

Modelling to inform the COVID-19 response in Bangladesh

AUTHORS: Elaine A Ferguson^{1*}, Eric Brum², Anir Chowdhury³, Shayan Chowdhury³, Mikolaj Kundegorski¹, Ayesha S Mahmud⁴, Nabila Purno⁵, Ayesha Sania⁶, Rachel Steenson¹, Motahara Tasneem², Katie Hampson¹

¹University of Glasgow, UK

²FAO, Bangladesh

³a2i, Bangladesh

⁴University of California, Berkeley, USA

⁵UNFPA, Bangladesh

⁶Columbia University, USA

*elaine.ferguson@glasgow.ac.uk

Abstract

Background: Non-pharmaceutical interventions (NPIs) used to limit SARS-CoV-2 transmission vary in their feasibility, appropriateness and effectiveness in different contexts. In Bangladesh a national lockdown implemented after the first detected case in early March 2020 rapidly exacerbated poverty and was considered untenable long-term, whilst surging cases in 2021 warranted renewed NPIs. We examine potential outcomes and costs of NPIs considered appropriate and feasible to deploy in Dhaka over the course of the pandemic including challenges of compliance and scale up.

Methods: We developed an SEIR model for application to Dhaka District, parameterised from literature values and calibrated to death data from Bangladesh. We discussed scenarios and parameterizations with policymakers using an interactive app, to guide modelling of lockdown and post-lockdown measures considered feasible to deliver; symptoms-based household quarantining and compulsory mask-wearing. We examined how testing capacity affects case detection and compared deaths, hospitalisations relative to capacity, working days lost from illness and NPI compliance, and cost-effectiveness.

Results: Lockdowns alone were predicted to delay the first epidemic peak but were unable to prevent overwhelming of the health service and were extremely costly. Predicted impacts of post-lockdown interventions depended on their reach within communities and levels of compliance: symptoms-based household quarantining alone was unable to prevent hospitalisations exceeding capacity whilst mask-wearing could prevent overwhelming health services and be cost-effective given masks of high filtration efficiency. The modelled combination of these measures was most effective at preventing excess hospitalizations for both medium and high filtration efficiency masks. Even at maximum testing capacity, confirmed cases far underestimate total cases, with saturation limiting reliability for assessing trends. Recalibration to surging cases in 2021 suggests limited immunity from previous infections and the need to re-sensitize communities to increase mask wearing.

Conclusions: Masks and symptoms-based household quarantining act synergistically to prevent transmission, and are cost-effective in mitigating impacts. Our interactive app was valuable in supporting decision-making in Bangladesh, where mask-wearing was mandated early, and community teams have been deployed to support household quarantining across Dhaka. This combination of measures likely contributed to averting the worst impacts of a public health disaster as predicted under an unmitigated epidemic, but delivering an effective response at scale has been challenging. Moreover, lack of protection to the B.1.351 variant means messaging to improve mask-wearing is urgently needed in response to surging cases.

Key words: Coronavirus disease 2019 (COVID-19); Non-pharmaceutical interventions (NPIs); Low- and middle- income countries (LMICS); Cost-effectiveness; Lockdown; Facemasks; Household quarantine; SEIR model

Introduction

Human infections with severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), the virus that causes the respiratory disease COVID-19, were first observed in China in December 2019¹. By the end of 2020, more than 80.3 million cases and 1.77 million associated deaths had been reported worldwide². With limited treatment options, countries turned to a range of non-pharmaceutical interventions (NPIs) to limit transmission. These measures include improved hygiene practices, social distancing, contact tracing, travel restrictions, quarantines, shielding of the vulnerable, lockdowns of differing severity, and facemasks. NPIs have been used by high-income countries (HICs) and low- and middle-income countries (LMICs) alike, but for a variety of reasons some of these measures may be less effective or more difficult to maintain in LMICs. Vaccines have come into play in 2021, but rollout has been almost exclusively in HICs. With negligible vaccination coverage and only NPIs to mitigate impacts, LMICs are now facing subsequent epidemic waves of faster-spreading variants and may have little protective immunity from prior infections^{3,4}.

Lockdowns can control COVID-19 epidemics by reducing the effective reproduction number, R_e , to below one⁵. However, where many people live precariously without social support, lockdowns can exacerbate poverty^{6,7} and risk food security, whilst poor adherence limits their effectiveness. Social distancing may be impractical in densely populated areas^{8–10}, hindered by larger household sizes and/or cramped conditions¹¹. Urban slums and refugee camps, where rapid transmission and poor healthcare access co-occur, present a particular concern^{12,13}. Shielding the most vulnerable, primarily older people and those with underlying health conditions¹⁴, is also challenging in multi-generational households^{15–17}. Contact tracing is limited by testing capabilities (facilities, trained personnel, consumables, reagents and biosafety)^{10,18,19} and information management capacity. Moreover, in settings where healthcare resources are already stretched, surge capacity is also low²⁰.

Some features of LMICs may mitigate the health costs of any lowered efficiency of NPIs. The relatively younger populations in LMICs, with fewer underlying risk factors, means that a smaller proportion of cases are likely to be severe relative to HICs^{8,14,17}. There has been speculation that the BCG (Bacillus Calmette-Guérin) vaccine, which is no longer routinely used in HICs, but is widely used in LMICs, may confer some protection from severe COVID-19, but evidence from trials is needed to confirm any association²¹. More generally, the wider social and economic consequences of NPIs may trade off against their impact on controlling disease, and the structure and underlying health of populations may impact the shape of this trade-off²². Hence, there is an urgent need for the development and implementation of contextually appropriate interventions that take into account the population that they target and their needs¹⁷.

During the pandemic, epidemiological models have received increased attention from governments and the public alike, and have influenced policy decisions worldwide²³. However, a translational gap persists between policymakers and scientists working on models for disease forecasting and assessment of interventions. Early in the pandemic, this gap was exacerbated by uncertainties about the biology and transmission of SARS-CoV-2, and the limited information about its spread, given local testing and reporting capacities, not to mention people's behaviour. As a consequence, there is often simultaneously both overconfidence in, and mistrust of, models.

Ideally, policymakers, scientists and communities should work together to develop and implement locally appropriate interventions. Models can play an important and overlooked role in facilitating this process. By empowering decision-makers to better understand the mechanisms underpinning the timescales and magnitude over which interventions lead to impact, as well as the uncertainties and social and behavioural factors that affect their efficacy, co-created models can inform short- and longer-term policies.

We investigate the potential impact of contextually appropriate NPI strategies to mitigate COVID-19 in Dhaka District, Bangladesh. High-density urban centres and refugee camps in Bangladesh led to fears that strained health systems would be quickly overwhelmed¹⁰. Cases of COVID-19 were first confirmed in Bangladesh on the 8th March 2020, and NPIs were subsequently introduced, beginning with postponements to mass gatherings, followed by international travel restrictions, and culminating in a national lockdown (announced as a ‘general holiday’) from 26th March^{10,12}. Rapid movement out of urban areas, particularly from the capital city Dhaka, following the lockdown announcement led to virus spread across the country¹⁰. The lockdown had swift economic repercussions: around 60% of households lost their main income source, the majority of previously vulnerable non-poor households slipped below the poverty line, and food security declined²⁴. The nationwide lockdown was quickly recognized as untenable long-term (ultimately ending on 1st June), and considered only as a stop-gap measure.

With input from policymakers, we developed an SEIR model to compare the potential of NPIs following the relaxation of lockdown. We designed an associated interactive app within which policymakers could explore these scenarios to gain an understanding of how the model worked and how uncertainties may influence outcomes. Here we compare scenarios based on projected 2020 COVID-19 deaths, and whether hospitalisations remain below capacity. We also explore associated costs and the importance of having NPIs in place by the time lockdown ends. Finally, we examine scenarios following resurgence of cases in March 2021 and a renewed lockdown and update our app for ongoing policy use.

Methods

Model description

We developed a deterministic SEIR model comprising a set of ordinary differential equations (ODEs) to describe SARS-CoV-2 transmission in Dhaka District, the most densely populated district in Bangladesh. Dhaka District includes rural areas in addition to the city area itself, but, as case data were resolved to district level, we consider the full district population, rather than restricting analyses to the city population.

The model includes three infectious states, with latently infected individuals either becoming pre-symptomatically infectious (I_p) before progressing to symptomatic infection (I_s), or becoming asymptotically infectious (I_a) until their recovery (Fig. 1). Susceptible individuals are exposed to SARS-CoV-2 according to transmission rates specific to each infectious state (β^a , β^p and β^s). These rates are based on: 1) asymptomatic individuals producing 65% of the secondary infections produced by pre-symptomatic-to-symptomatic individuals²⁵; 2) 35% of secondary infections from pre-symptomatic-to-symptomatic individuals happening in the pre-symptomatic period²⁶; and 3) the value of R_0 :

$$R_0 = f^a \beta^a d^a + (1 - f^a)(\beta^p d^p + \beta^s d^s)$$

where $d^a = 7$, $d^p = 2$ and $d^s = 7$ are the mean durations (in days) of each infectious state^{27,28}, and f^a is the proportion of infections that are asymptomatic (supplementary Table S4). Recovered individuals are considered to be immune.

We track numbers of both general and Intensive Care Unit (ICU) beds required by COVID-19 patients, and deaths due to COVID-19 (Fig. 1). A proportion of individuals $f^H(1 - f^{ICU})$ that leave

the pre-symptomatic state join a holding category prior to progressing to general hospital beds, while a second proportion $f^H f^{ICU}$ enters a holding category prior to entering ICU beds. Individuals remain in these two holding categories from the first appearance of symptoms until the point at which hospitalisation is required, on average 7 days^{29,30}. A third holding category retains a proportion of individuals f^D from the first appearance of symptoms until death, on average 20.2 days later^{29,31}. While we assume no overlap between the groups in ICU versus general hospital beds, overlap between those that die and the hospitalized groups is both permitted and expected. On leaving hospital, after a mean of 5 days for general beds and 7 days for ICU³², recovered individuals recuperate for an average of 3 weeks before resuming work, if employed³³. The number of individuals in the seven health outcome states has no impact on transmission dynamics, and it is assumed that there is no impact of a lack of hospital beds on the COVID-19 death rate. This approach to modelling health outcomes is similar to that described in several other COVID-19 models^{34,35}.

We use data on the age structure of the Dhaka population³⁶ (supplementary Table S1) to inform parameters describing the risks of SARS-CoV-2 infections. Previously estimated age-specific risk of death due to COVID-19, of hospitalisation for symptomatic cases³⁴, and of developing symptoms¹¹ (supplementary Table S2), were combined with the age distribution in Dhaka District, to estimate the overall proportions of 1) asymptomatic infections, $f^a = 0.701$, 2) symptomatic infections that lead to death, $f^D = 0.009$, and 3) symptomatic infections requiring hospitalisation, $f^H = 0.073$. Of those hospitalised we assume that the proportion requiring critical care in an ICU is $f^{ICU} = 0.31$ ³⁷. We assumed no age-structure in contacts within our model.

The model was initially developed as an interactive epidemiological teaching tool (http://boydorr.gla.ac.uk/BGD_Covid-19/CEEDS/), to allow policymakers to explore the impact of interventions on health outcomes and working days lost. For speed and efficiency, and given the large population (Dhaka District population in 2020 is around 13.8 million^{36,38}), the decision was made to make the model deterministic rather than stochastic. We minimise computational complexity by modelling transmission at the population level rather than at the level of the individual or household. However, to more accurately model household quarantining, we further subdivide the six disease states (Fig. 1) to track within-household transmission and account for household-level susceptible depletion (Supplement A).

The ODEs comprising the model are provided in Supplement A and the model parameter descriptions, values and sources, are listed in Supplementary Table S4. Analyses were implemented in R³⁹, with the ODEs numerically integrated using the package deSolve⁴⁰. Code can be accessed from our Github repository (https://github.com/boydorr/BGD_Covid-19/BGD_NPI_model).

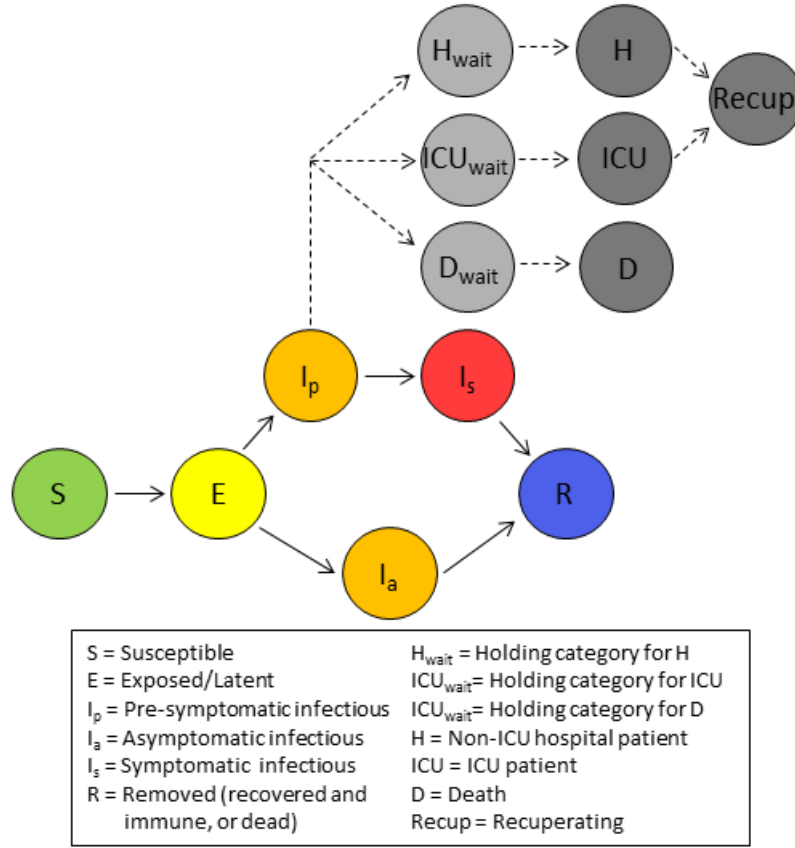


Figure 1: Model Schematic illustrating the movement of individuals between classes. Coloured circles indicate disease states that impact transmission. Grey circles describe health outcomes that are tracked but have no impact on disease transmission.

Interventions

We implemented three main NPIs – lockdown, household quarantining with support from Community Support Teams (CSTs), and mask wearing – that were considered to be feasible by policymakers in Bangladesh. For each intervention we considered timing of implementation, scaling up and levels of compliance. In real-time we explored these interventions with policymakers including the lockdown duration, however here we model lockdown as implemented (26th March to 1st June 2020) and consider additional lockdown extensions, which, despite their impracticality, allow comparison to more feasible scenarios.

We define a lockdown as a scenario where all except essential workplaces are closed, including educational facilities, and people are asked to stay home where possible and practice social distancing. For compliant individuals and those that are not essential workers, this intervention is assumed to reduce contacts, and therefore transmission, outside of the household by the proportion ϵ^{ld} , while leaving within-household transmission unchanged. We achieve this by breaking down the transmission rates for the three infectious states into within- and between-household components using estimates of the SARS-CoV-2 household secondary attack rate, $\sigma = 0.166^{41}$, and the mean household size, $\eta = 4^{42}$. We considered a scale-up period for the lockdown, during which compliance increased linearly from zero to a maximum. Following scale-up, we assume compliance starts to decline exponentially towards a minimum. Full details of implementation are given in Supplement A.

Under the household quarantine intervention, when a symptomatic individual occurs, the entire household of that individual is required to quarantine for 14 days. Those who develop symptoms can self-report to a national COVID-19 hotline or are identified by word-of-mouth, triggering a visit by CST, a volunteer workforce of community-based support workers trained by BRAC/FAO. The CST confirm that symptoms are syndromically consistent with COVID-19, provides education on how to limit spread, facilitates access to healthcare, and offers support to aid quarantine compliance, with additional follow-up conducted during the quarantine period.

Modelling household quarantine requires us to be able to identify both those individuals that trigger quarantining (the first symptomatic individuals within households), and individuals in the household who will also undergo quarantine. We subdivide the disease states to identify those that are not currently in an infected household, those that are in a non-quarantined infected household, and those that are in a quarantined household. When a susceptible individual in an uninfected household becomes latently infected (through between-household transmission), $\eta - 1$ other individuals also move from uninfected household categories into categories that identify them as being in a non-quarantined infected household, making them vulnerable to both within-household and between-household transmission. We track the group of individuals who were the first infected within a household separately to those who subsequently became infected, allowing us to observe when household index cases become symptomatic. A proportion of these symptomatic index cases comply with quarantine, taking $\eta - 1$ individuals from non-quarantined infected households with them. We also trigger quarantines when within-household cases resulting from index asymptomatic cases become symptomatic. The equations generating these dynamics are described in Supplement A. Infectious individuals within quarantined households are assumed to not cause any between-household transmission. As with lockdown, household quarantining with CST support has defined start and end times, and the proportion of households that comply increases linearly through a scale-up period, after which compliance remains at a constant maximum (see Supplement A).

Finally, we considered compulsory mask-wearing outside of the household. Within the model, masks are assumed to block a proportion, ε^m , of between-household transmission from compliant individuals, while also blocking a proportion, $\varepsilon^m \rho^m$, of transmission to compliant individuals, where $0 \leq \rho^m \leq 1$, i.e. masks protect others from the wearer, and the wearer from others, to different degrees, with protection provided to the wearer never greater than that provided to others^{43,44}. The full description of mask wearing effects, in relation to timing and compliance is provided in the Supplement A.

We model working days lost due to both illness and interventions. Based on the 2011 census³⁶, we assume 52% of the population is formally employed, working five days a week. We model symptomatic and recuperating individuals to be off-sick, and assume that deaths result in loss of all subsequent working days through 2020. During lockdown, those workers that are both compliant and not essential workers lose their working days. Those in quarantined households do not work, and, since household quarantine is based on symptoms, we assume that, in addition to those quarantined due to COVID-19, a proportion of households affected by non-COVID-19 influenza-like illnesses also undergo quarantine. Based on the 2011 census, 23% of the population is unemployed, but works within the household, e.g. with caring responsibilities³⁶. When these individuals are hospitalised or die, we assume another (possibly formally employed) household member replaces them, leading to further loss of working days. Finally we assume that, in response to each death, a number of grieving individuals (taken to be $\eta - 1$) do not work for a week. Details of the working days lost calculation are provided in equations S.16-17.

Scenario comparison

With input from policy-makers, we explored 15 combinatorial scenarios for the year 2020, including a baseline with no interventions and unmitigated SARS-CoV-2 spread.

The first of four lockdown-only scenarios aimed to replicate the lockdown as implemented, from 26th March until 1st June 2020. The other three lockdown-only scenarios involved extending the lockdown by 1, 2 and 3 months. In all four scenarios we assume scale-up occurs over one week, with peak compliance of 80%, declining towards 30% (Fig. S1D); considered to be qualitatively similar to practice in Dhaka. The impact of lockdown on between-household transmission of compliant individuals ε^{ld} was estimated during model calibration (see below).

We also examined a scenario where the lockdown, as implemented in Bangladesh, was followed by CST interventions beginning a week before lockdown ended, and continuing through 2020 with a 7-day scale-up period and 80% peak compliance. In addition to this scenario, we examined compulsory mask-wearing with the same timings and compliance. However, the ability of masks both to protect others from transmission from the wearer and to protect the wearer from transmission from others depends on several variables, including the material used, the construction (e.g. layers of material), and the quality of fit^{43,45,46}. Therefore, we consider scenarios where there is low, medium, and high protection of others from the wearer ($\varepsilon^m = \{0.2, 0.5, 0.8\}$), and where the protection provided to the wearer is zero, half that provided to others, or equal to that provided to others ($\rho^m = \{0, 0.5, 1\}$), giving nine mask-wearing scenarios. Finally, we consider lockdown as implemented, followed by both household quarantining and mask-wearing, under the same combinations of settings and mask protectiveness.

For the 2020 time horizon we compared the total: 1) hospitalisations, 2) deaths, 3) percentage of patient days exceeding hospital capacity (the sum of patients in excess of hospital beds each day, divided by the summed total patients over all days), 4) working days lost, 5) health provider costs of care for COVID-19 patients and implementing interventions, 6) health provider costs per death averted (relative to no intervention), and 7) the percentage return (in terms of healthcare savings) on investment (%ROI) in interventions. For estimating the health provider costs we include healthcare provision, media campaigns, training and deployment of CSTs, and mask distribution, as detailed in Table 1. For each scenario, we used total costs to estimate the cost per death averted. This was calculated by subtracting the cost of the baseline scenario from the focal scenario, then dividing by the reduction in deaths from the baseline. The %ROI for each scenario was calculated by subtracting the total cost of each scenario from the baseline, and dividing by the intervention implementation costs.

Given the heavy societal and economic costs of lockdowns, they are typically viewed as temporary measures to buy time for implementation of other less restrictive measures (e.g. mask wearing) or more targeted measures (e.g. household quarantines and contact tracing). To explore the impact of preparedness prior to lockdown ending, we examined the sensitivity of model outcomes (hospitalisations, deaths, working days lost, and exceeded hospital capacity) to the scale-up period and start date of post-lockdown interventions. Modelling lockdown as implemented in Bangladesh, we looked at scenarios where lockdown was followed by household quarantining only, mask-wearing only (assuming mask protectiveness parameters $\varepsilon^m = 0.5$ and $\rho^m = 0.5$), or both. We varied the start date of the post-lockdown intervention(s) from 30 days pre- to 30 days post-lockdown ending, while keeping the scale-up period constant at 7 days, and vice versa varying the scale-up period (zero to 30 days), while keeping the start constant (7 days prior to the lockdown end).

Table 1: Costs associated with healthcare and interventions.

Item	Description of activities	Costs (USD)
Hospital care	Provision of hospital beds and associated care for severely ill COVID-19 patients, including ICU, mechanical ventilation, oxygen etc.	\$200/day/patient (high cost scenario) \$50/day/patient (low cost scenario)
Community Support Team (CST) package	The CST package covers: <ul style="list-style-type: none"> - community health worker training and equipment - monthly per volunteer running costs, covering honorarium, phone credit, PPE for activities and management. Each volunteer can visit 20-40 quarantining households per day. Plans are to train 2000 volunteers, which should be sufficient to cover the Dhaka District population.	\$200/volunteer trained and equipped \$240/month/volunteer running cost
Masks	Free re-usable cloth masks provided to the full Dhaka District population, and mask wearing promoted through a public awareness campaign. Both high (2 masks/person) and low (1 mask for 50% of people) cost scenarios are considered	\$1.2/mask \$150,000 media campaign
Lockdown	Public awareness campaign to encourage people to remain at home and practice social distancing.	\$150,000 media campaign

Model calibration

We calibrated two parameters, R_0 and ε^{ld} , the proportion by which lockdown reduces between-household transmission from compliant people, against daily COVID-19 death data in Bangladesh⁴⁷. We chose to calibrate against reported deaths rather than cases, since death data are less affected by testing and reporting capacity. To obtain a time-series of deaths in Dhaka District, we extracted the proportion of district-resolved case totals for Dhaka District from Bangladesh's COVID-19 dashboard⁴⁸ and assumed this proportion remained constant. The first three cases in Bangladesh were confirmed on 8th March 2020, but it is thought likely that infection began circulating undetected prior to this, with genomic data indicating an introduction in mid-February and at least eight introduced cases prior to the ban on international travel⁴⁹. We therefore initialise the model with eight infectious cases on 15th February 2020. To calibrate R_0 , we ran the model with R_0 equal to 2.7³⁴ and calculated the absolute difference between the modelled cumulative deaths and the data on the date lockdown started (26th March), then adjusted R_0 (up to two decimal points) to

minimize the difference between modelled deaths and data. Following selection of R_0 , the value of ε^{ld} was similarly estimated by minimizing the difference between modelled deaths and data on the date lockdown ended. We recalibrated the model to death data from March 2021 to re-estimate R_0 under the resurgence (given potentially different characteristics of B.1.351 variant). Estimates were obtained under different assumptions of pre-existing immunity (0%, 25% and 50%) and circulating cases, specifically that new daily cases represent around 10% of true cases, and case numbers could be 50% higher or lower than this best guess.

Sensitivity Analyses

There is considerable uncertainty in the parameters governing SARS-CoV-2 transmission and health impacts. We therefore undertook one-way sensitivity analyses across parameter value ranges for R_0 , the duration of disease states and health outcome stages, the introduction date, the household secondary attack rate, the ratios of asymptomatic to symptomatic transmission, and of pre- versus symptomatic transmission identified as plausible from the literature (supplementary Table S4), assessing the main model outputs while keeping other parameter values fixed. We ran this analysis over: 1) no interventions; 2) lockdown as implemented; 3) lockdown plus household quarantining; and 4) lockdown plus compulsory mask wearing (with $\varepsilon^m = 0.5$ and $\rho^m = 0.5$).

Results

Model calibration

We estimated that $R_0 = 3.57$ for transmission of SARS-CoV-2 in Dhaka in 2020, and that the lockdown reduced between-household transmission (ε^{ld}) by 97% for compliant individuals. The match between modelled deaths and data during the early stages of the epidemic is illustrated in Fig. S1A and B). Outputs from the calibrated model until the lockdown end indicate that less than 10% of cases were recorded during this period (Fig. S1C). We further explored how testing capacity might impact case detection within our interactive app, which similarly indicated that the low, but increasing, testing capacity in Dhaka would fail to detect a high proportion of cases given the high proportion of asymptomatic cases and distribution of tests to individuals with other influenza-like illnesses. Our best estimate of R_0 (3.5) was similar in 2021, under the assumption of 25% immunity from prior infections. However this estimate is sensitive to uncertainty in initial circulating case numbers and levels of acquired immunity, with possible values ranging from 2.3-6.5 (Supplementary Table S5).

Impacts of scenarios on health outcomes and working days lost

In the absence of interventions we predicted that COVID-19 patients would peak at 46,309 in late May (Fig. 2A), greatly exceeding hospital bed capacity (estimated to be 10,947 in Dhaka District⁵⁰; Table S4). Under this scenario hospital beds would have been unavailable for at least 55% of patient days (Fig. 3D) without accounting for non-COVID-19 bed needs. Assuming unmitigated transmission, the epidemic would have likely led to around 13.3 million cases (i.e. most of the Dhaka District population; Table S4) and 35,849 deaths (Figs. 3A, S2A & S3A). Although high relative to some of the mitigated scenarios, these deaths only represent 0.26% of the population, and might lead to a loss of <1% of total working days (Fig. 3C).

We forecast that the lockdown as implemented in Bangladesh would delay the epidemic (Figs 2A and S2A), with minor impacts on deaths and hospitalised cases (Fig. 3), while increasing working days lost to 9.6%. Extensions were predicted to delay and widen the peak (Figs 2A and S2A, extensions shown for up to three months, as further extensions had little impact on the epidemic peak or total outcomes). Even with lockdown extensions, hospitalisations were still expected to outstrip capacity (Fig. 2A), with only modest reductions in deaths (Fig. 3). Working days lost were predicted to increase by 2.5-3.5% with each extra month of lockdown (Fig. 3C).

We found that introducing household quarantining following lockdown led to the epidemic peak being later, lower and wider than with lockdown alone (Figs 2A and S2A). Hospital capacity was still exceeded, with deaths and hospitalisations reduced to levels similar to those achieved by a three-month extension to lockdown. The additional working days lost by introducing and maintaining household quarantines throughout 2020 were fewer than those lost by a one-month lockdown extension (Fig. 3C).

The impact of introducing compulsory mask-wearing following lockdown varied based on the effectiveness of the masks used (Figs 2B and 3). When $\varepsilon^m = 0.2$, i.e. low filtration efficiency, only relatively small reductions to the epidemic peak were predicted, with the decline increasing with mask effectiveness in terms of PPE (indicated by increasing ρ^m ; Figs 2B and S2B). Masks with high filtration efficiency ($\varepsilon^m = 0.8$), or medium filtration efficiency combined with high PPE efficiency ($\varepsilon^m = 0.5$, $\rho^m = 1$) flattened the peak sufficiently to keep patient numbers below hospital capacity (Figs 2B and 3D). Effective masks also led to substantial drops in deaths and hospitalisations, while slightly reducing working days lost relative to the lockdown-only scenario (Fig. 3).

Combining mask-wearing with household quarantine led to greater predicted reductions in the epidemic peak and in both deaths and hospitalisations than either intervention alone (Figs 2C and 3A-B). Percentages of working days lost increase as mask quality decreases, ranging from 8.8-11.2%. A combined strategy of masks and quarantine following lockdown was what was ultimately implemented in Dhaka District. The data-based estimates of cumulative deaths in Dhaka District take a path similar to those modelled by combining quarantining with either masks of high filtration effectiveness ($\varepsilon^m = 0.8$) and low to medium PPE abilities (ρ^m of 0 or 0.5), or with masks of medium filtration effectiveness ($\varepsilon^m = 0.5$) and $\rho^m = 1$ (Fig. S3C).

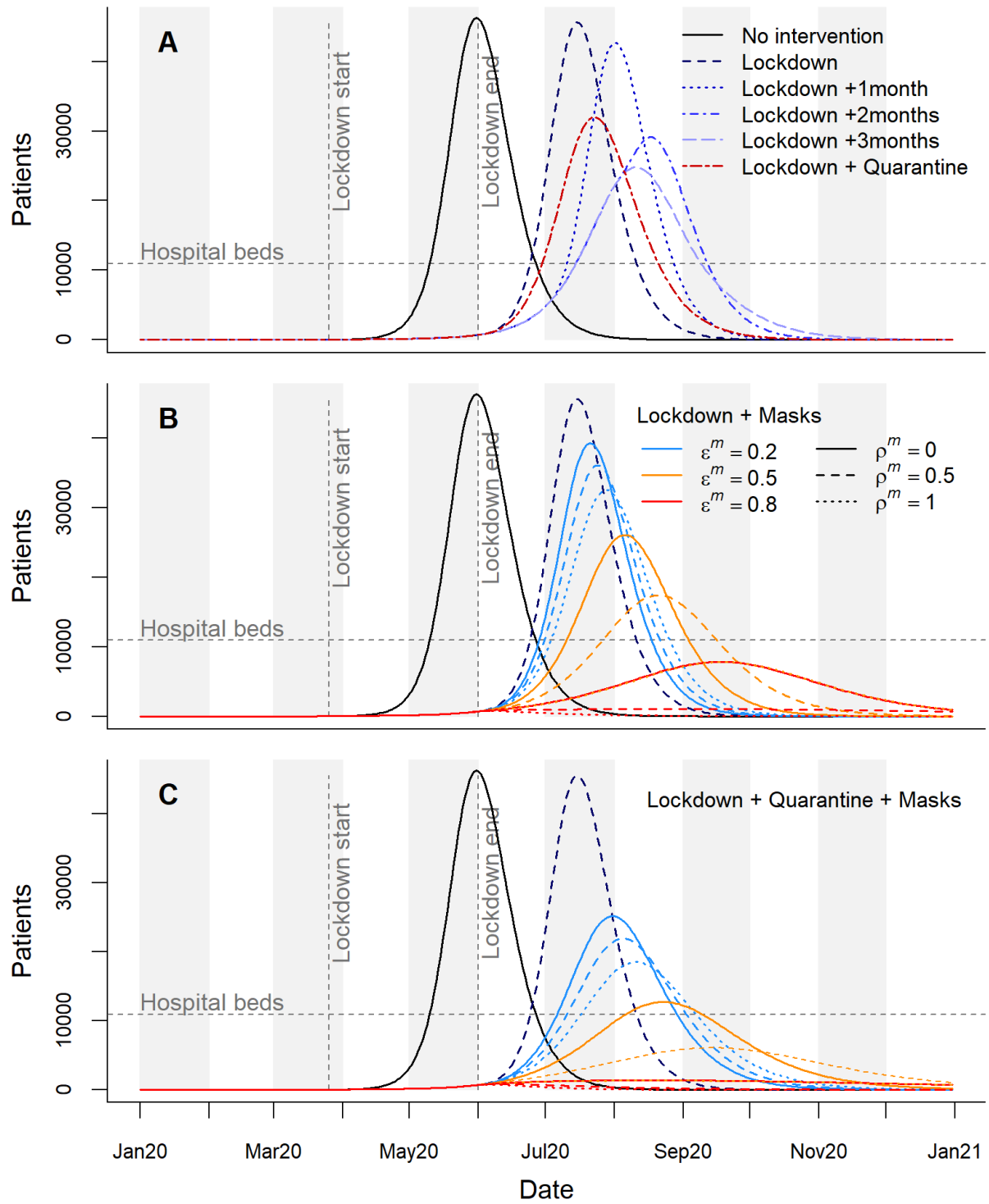


Figure 2: Time series of hospital patients for intervention scenarios in 2020. Horizontal dashed lines indicate hospital bed capacity in Dhaka District. Vertical lines indicate the start and end points of lockdown as implemented in Bangladesh. A) Hospital patients in the absence of interventions, for the implemented lockdown plus extensions of up to 3 months, and for lockdown followed by household quarantine with community support teams. B) Lockdown as implemented followed by compulsory mask wearing, considering nine mask effectiveness scenarios; ϵ^m describes the proportion reduction in outward emissions by mask wearers, while $\rho^m \epsilon^m$ describes the proportion protection to mask wearers from others' emissions. C) Combined impacts of the lockdown, household quarantine, and masks of different effectiveness.

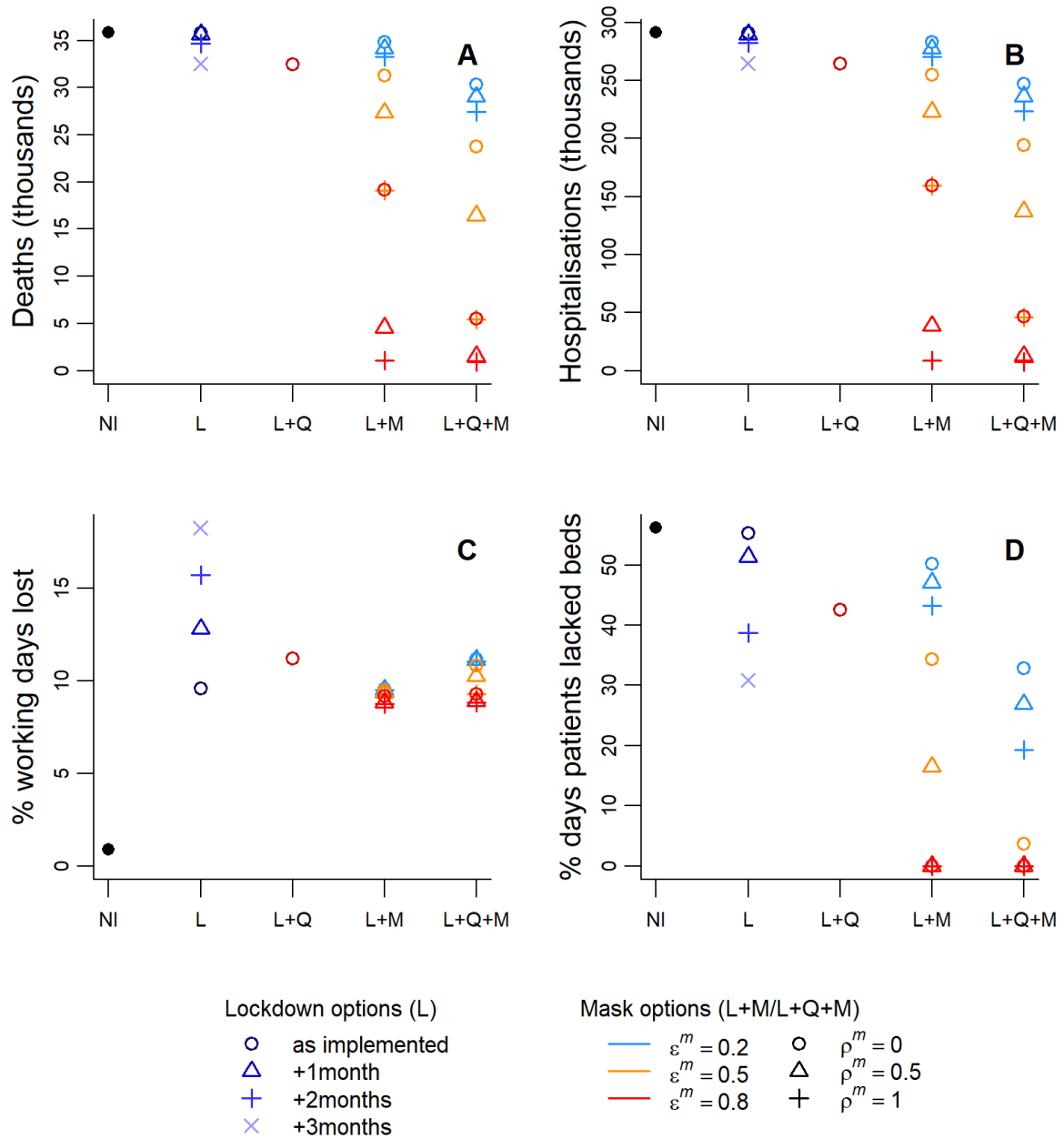


Figure 3: Summaries of health outcomes and working days lost for a range of interventions during 2020. NI=no intervention, L=lockdown, Q=household quarantine with community support teams, M=compulsory mask wearing. ε^m describes the proportional reduction in outward emissions by mask wearers, while $\rho^m \varepsilon^m$ describes the proportion protection provided to the mask wearer from others' emissions.

Scenario costs

The ranking of scenarios in terms of their total cost to the government remains relatively consistent between the high and low cost scenarios, with estimated costs ranging from \$11.0-351.4 million (Fig. 4A). Despite requiring no direct intervention costs, the baseline scenario is among the most expensive due to the healthcare costs incurred by hospitalisations. Lockdown as implemented was predicted to be similar in cost to the baseline (unmitigated transmission) with modest declines for lockdown extensions. Incorporating household quarantine led to costs similar to the longest

extended lockdown. Combining lockdown with low effectiveness masks led to the highest costs due to the expense of mask distribution, offset by only small reductions in healthcare costs. Masks of high effectiveness, however, led to substantial cost reductions, which increased when masks and household quarantine were modelled together.

Since most scenarios had a lower total cost than the baseline, the cost per death averted is negative except in the combined lockdown and low effectiveness mask scenarios (where the cost per death averted ranges from \$1070-\$22,708 according to mask type and cost scenario), and in the low-cost basic lockdown scenario (Fig. 4B). Extended lockdowns, and lockdowns combined with household quarantine and/or high effectiveness masks all provide similar savings per death averted in the \$7000-\$9000 range for the high cost scenario, but considerably lower for the low cost scenario. More modest savings per death averted were provided by the lockdown as implemented, medium effectiveness masks, and low-medium effectiveness masks combined with quarantine. The %ROI was generally positive, with the same exceptions that had positive costs per death averted (Fig. 4C). By far the highest %ROIs were given by extending lockdown by 2-3 months. This is because, despite relatively small reductions in hospitalisations (Fig. 3B), there are no direct costs to lockdown extension (Table 1). Lockdown plus quarantining gave a %ROI of 655% for the high cost scenario and 89% for the low cost scenario. The %ROI of all scenarios involving masks increased with the effectiveness of the masks in blocking transmission. In the high cost scenario, most interventions involving masks (with the exceptions of the two highest effectiveness mask types) had a lower %ROI than the lockdown plus quarantine scenario, while in the low cost scenario this was only true of interventions involving the 3-4 lowest effectiveness mask types.

Intervention timing and scale-up

Starting either household quarantining or compulsory mask-wearing prior to the end of lockdown had little projected impact on health outcomes or the percentage of working days lost (Fig. 5A-D). When masks and quarantining are combined, however, total deaths and hospitalisations are seen to decline in response to moving their start dates further before the end of lockdown. This difference occurs because the combined early start date of the two interventions pushes the epidemic peak later (into 2021) than when considering either individually. Continuing interventions and calculating outcomes over both 2020 and 2021, removes this apparent improvement in outcomes with start dates prior to lockdown's end (Fig. S4A-D). As the start date of quarantining and mask-wearing is delayed beyond the lockdown end date, their health benefits decline, with all outcomes approaching those of the lockdown-only scenario. Similar consequences to delaying intervention start dates result from lengthening the scale-up period (Fig. 5E-H).

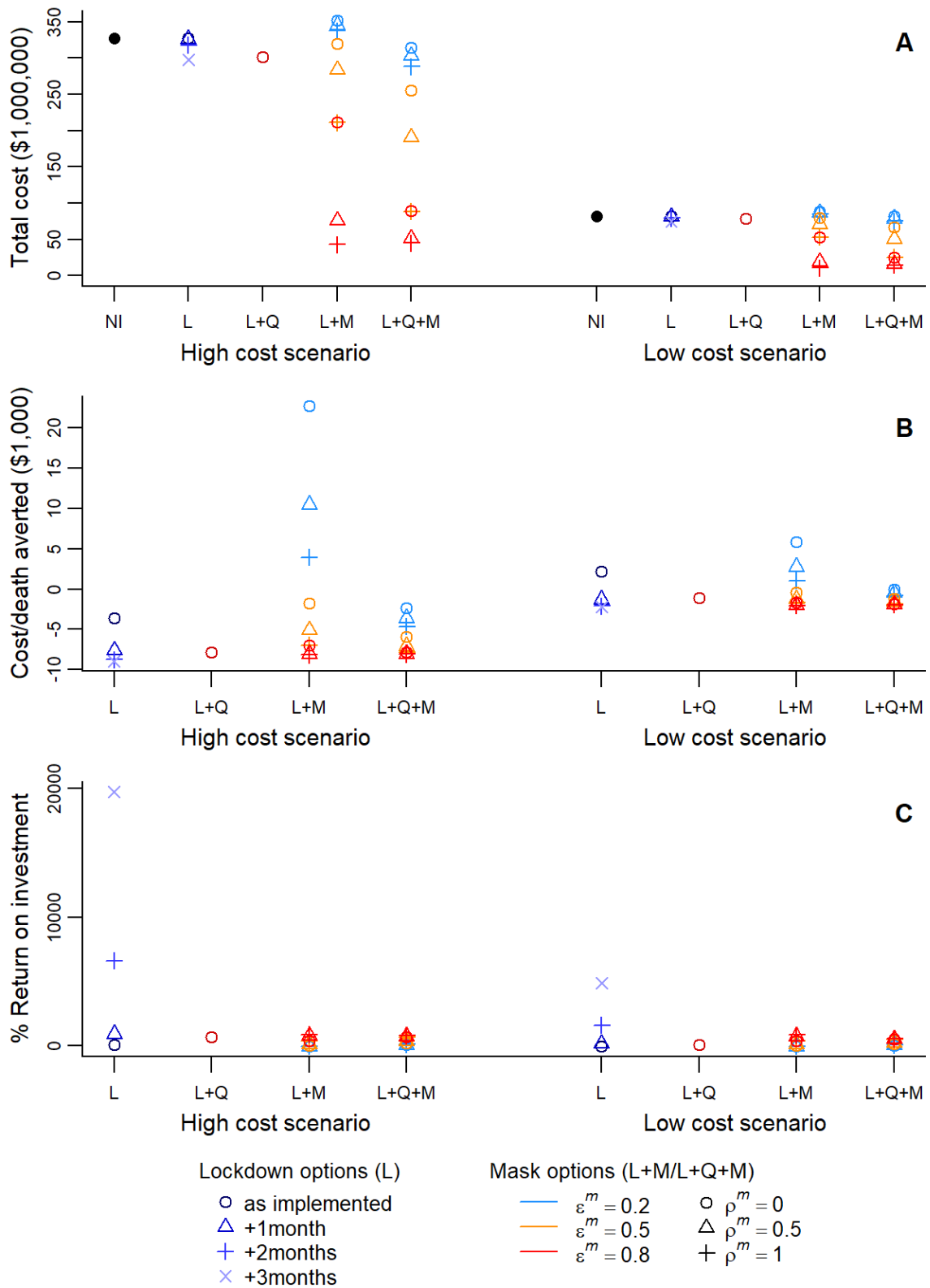


Figure 4: Costs of intervention scenarios. NI=no intervention, L=lockdown, Q=household quarantine with community support teams, M=compulsory mask wearing. ε^m describes the proportional reduction in outward emissions by mask wearers, while $\rho^m \varepsilon^m$ describes the proportion protection provided to the mask wearer themselves from others' emissions. A) Total cost of each intervention scenario to the government based on costings in Table 1. B) Cost of each death averted relative to the baseline (NI) scenario. C) Percentage return on investment in interventions in terms of healthcare savings.

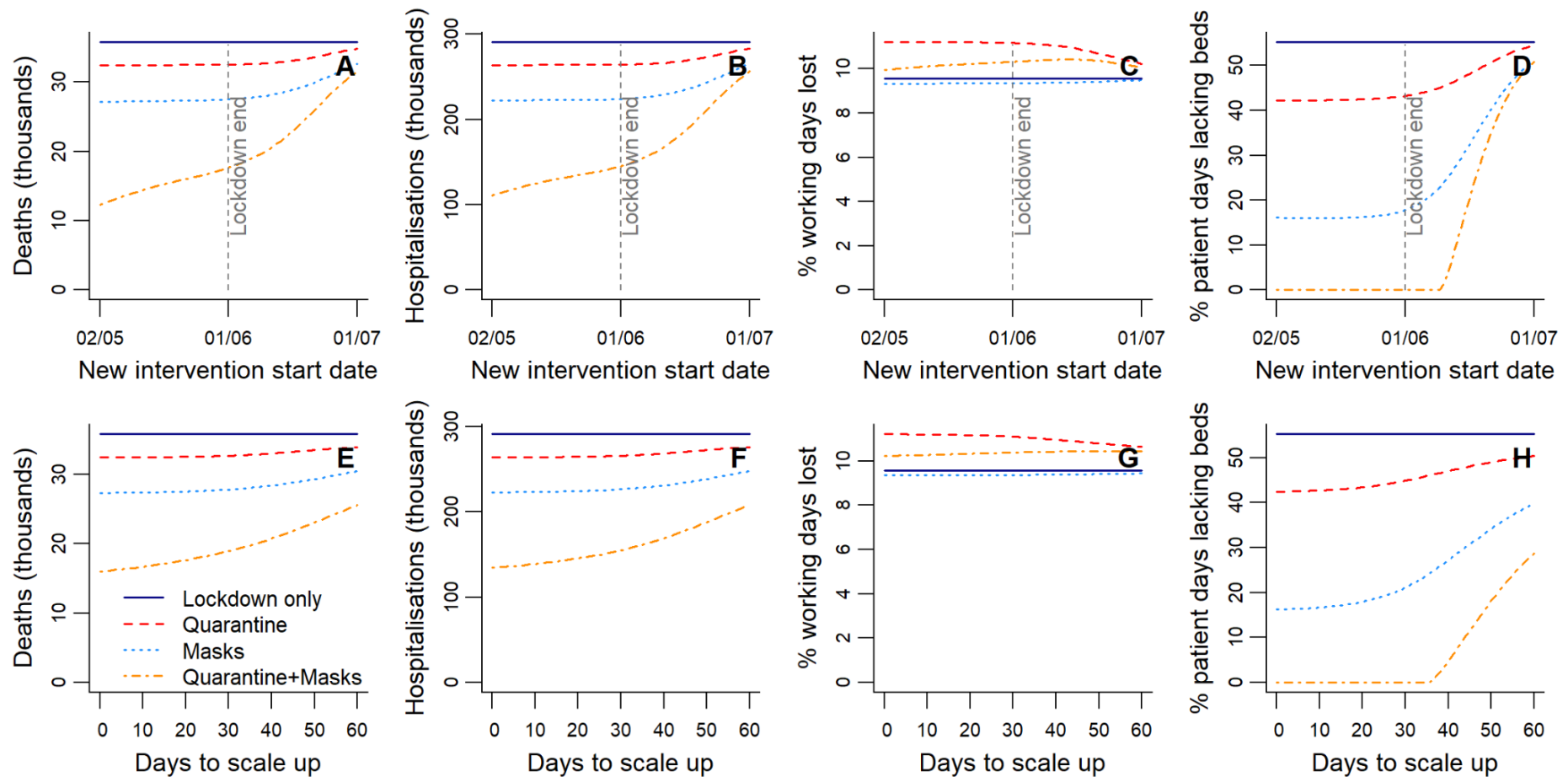


Figure 5: Sensitivity to the start date and scale-up period of quarantine or mask wearing following lockdown. A-D) Changes in health outcomes and working days lost over 2020 when the start date of interventions (household quarantine, masks, or quarantine and masks) following lockdown is adjusted relative to the lockdown end date. The days taken to scale up interventions to their full effectiveness is held constant at seven days. E-H) Changes in the same outcomes when the time in days taken to scale up post-lockdown interventions is varied. The start date of the post-lockdown interventions is held constant at seven days prior to the lockdown end date.

Sensitivity Analyses

R_0 was among the top three most influential parameters for all five outcome measures reported under all four baseline scenarios (Figs. S5-8). The duration of symptoms was among the top three most influential parameters in determining working days lost (since symptomatic people are unable to work) over all baselines, and, predictably, the mean lengths of stay in general hospital and ICU beds were highly influential for the percentage of patient days that lacked beds. For all baselines, other than that with no interventions, the introduction date of the disease ranked in the top three most important parameters for all outcomes except the percentage of patient days lacking beds. Some parameters only gained importance under specific baseline scenarios (for example, the level asymptomatic transmission becomes important under symptoms-based household quarantine); for more details see Supplement D.

Discussion

We modelled interventions for controlling COVID-19 transmission in Dhaka District, Bangladesh, comparing them based on their ability to prevent both deaths and overwhelming of the health system, as well as on their societal and health provider costs. We found that under expected compliance, lockdowns alone, regardless of duration, were both costly and unable to keep cases below hospital capacity, while preventing only a small proportion of deaths, confirming that they are not an appropriate long-term measure in this context^{6,7,24}. Additional quarantining of households with symptomatic individuals similarly was not predicted to prevent hospitalisations exceeding capacity. Modelling compulsory mask-wearing after the lockdown produced outcomes that varied widely depending on the effectiveness of masks in blocking transmission. Low-quality masks had limited impacts and were not cost-effective, whereas high-quality masks substantially reduced deaths, protected the healthcare system and were cost-effective. Combining mask-wearing and household quarantine led to further reductions in deaths and excess hospitalisations, and was cost effective. Simulations also suggest that early introductions of post-lockdown measures would have had negligible additional impact over the full course of the epidemic (though they may improve outcomes in the short-term), but gaps between lockdown ending and post-lockdown interventions (or long periods of scale-up) quickly dilute their impacts.

The inability of symptomatic household quarantining alone to prevent hospitalisations exceeding capacity is unsurprising. Even in HICs with greater healthcare capacity, lower R_0 estimates, and a lower proportion of asymptomatic transmission, other modelling studies have suggested that symptoms-based household quarantine would still overwhelm health systems^{51,52}. Additional tracing and quarantine of non-household contacts of symptomatic individuals can improve the effectiveness of quarantine measures⁵¹. However capacity for extensive contact tracing is likely to be limited in high-density resource-constrained settings like Dhaka. The finding that combining symptomatic household quarantining with mask mandates (using mid- to high-quality masks) leads to effective control was crucial at the time, since both these NPIs were considered feasible. Given that household quarantining is triggered by a symptomatic case, and we estimate that most cases in Bangladesh are asymptomatic, a large proportion of infectious households are still likely missed by this measure, which will also have only limited impact on pre-symptomatic

transmission. Since masks reduce transmission for all infections, irrespective of symptoms, masks work synergistically with household quarantine. While we consider scenarios where masks block <20% of transmission, we note that this is a worst case scenario; experimental work suggests that our mid- to high-quality mask scenarios (blocking 50-80% of transmission) are more likely^{45,46}. Observational^{53,54} and other modelling⁴⁴ studies provide further evidence for the effectiveness of masks in blocking transmission.

In reality, achieving the modelled effectiveness of household quarantining and mask-wearing depends on high compliance (we assumed 80% compliance in results presented here). A survey in Israel suggested that quarantining compliance is likely to be highly dependent on compensation for loss of work⁵⁵. However, such compensation may be unachievable in many LMICs. Reducing insecurity experienced by households under quarantine in other ways, for example by food provisioning and healthcare access, may help mitigate income loss and boost compliance amongst poorer households. In Bangladesh, CSTs are already playing this role in supporting quarantining households, and in LMICs more broadly, community health workers are likely to prove invaluable in using the trust they have established to encourage compliance with NPIs⁵⁶.

Most of the NPIs we explored were very cost-effective, with savings per death averted and a positive %ROI as a consequence of the high contribution of healthcare to overall costs. Note that these returns occur despite the relatively young population in Bangladesh, which leads to a low proportion of hospitalized cases (0.022). Furthermore, the societal costs (in terms of working days lost) of the post-lockdown NPIs considered were small when compared with the initial lockdown costs and potential extensions. These findings are in line with other work showing that the costs of unmitigated transmission exceed those of implementing NPIs^{20,57}. The costs we explore here are based on crude assumptions for mask purchase and costs of training and rollout of CSTs in Dhaka where there is already a large community health workforce that can be mobilized. However, we do not include food packages or additional support for vulnerable communities that may increase NPI effectiveness but also costs.

Throughout the development of our model and interactive app, we incorporated suggestions from policymakers on questions that most urgently needed answers, and on NPIs under consideration and thought feasible to implement. This co-development allowed the investigation of scenarios appropriate to the local context that addressed pressing policy concerns²³. The app, which allows a user-friendly exploration and visualisation of how scenarios impact health outcomes and costs, proved to be an effective tool to support discussions with policymakers, as the timing and combination of interventions, along with uncertainties in parameters, including compliance, could be explored on the fly. This proved to be crucial in understanding the economic and health trade-offs involved, as well as helping to demystify the model itself and the ensuing epidemic.

Our study has a number of limitations. First, to ensure our model could run sufficiently quickly for the interactive app, stochasticity and individual variation in transmission was not incorporated. We expect only a minimal impact of these simplifications on disease trajectories and key results due to the large population size considered and rapid epidemic growth observed. However, they do limit the usefulness of the model for exploring elimination scenarios, since stochasticity and superspreading, inherent to SARS-CoV-2 transmission⁵⁸, become more influential under low levels of infection⁵⁹. Imported infections, which may similarly become important near

elimination, were also not considered. Age-structured models have been proposed for studying COVID-19^{34,35,52}. We did not include age-structured transmission, which though not entirely realistic, may be reasonable given the high degree of intergenerational mixing in Bangladesh¹⁶ and some other LMICs¹⁷. We also do not consider exacerbated mortality when hospital capacity is exceeded, potentially underestimating mortality under some scenarios. Parameters used for case fatality, and proportions of symptomatic and hospitalised infections, were based on age-dependent estimates from HICs^{11,34} and the age-distribution in Dhaka District. However, these HIC-derived parameters may be less accurate when applied in this setting, as the incidence among age classes of underlying conditions that increase COVID-19 risk likely differs in LMICs¹⁴. We also note that our estimates of working days lost make the assumption that employed people cannot switch to working from home, possibly leading to overestimation.

Our initial model assumed that recovered individuals remain immune through 2020. Although immunity to SARS-CoV-2 is not permanent⁶⁰, this assumption appeared reasonable given effects of immunity loss were likely to have been limited over this period. However, with the resurgence of cases in 2021 concomitant with the emergence of the B.1.351 variant the question of immunity became paramount^{61,62}. Assuming around 25% of the population had immunity gave reasonable R_0 estimates. This percentage is lower than expected given model predictions and observed case numbers in 2020, but in line with laboratory evidence suggesting that prior COVID-19 infections elicit reduced protection to the B.1.351 variant. Relaxation of NPIs coinciding with vaccine introduction and increased transmissibility of B.1.351 likely contributed to the resurgence, warranting further exploration and more data to more accurately quantify these features.

More generally there remains considerable uncertainty around many of the model parameters. Our sensitivity analyses indicated that R_0 was, predictably, very influential in determining health outcomes, but is sensitive to the introduction date and number of imported cases which are uncertain. In addition, prior to the lockdown, only 5 deaths due to COVID-19 had been recorded in Bangladesh, and given the inherent stochasticity in these events, tuning R_0 to data in this time window is unlikely to be very accurate. Finally, prior to the lockdown, some control measures, such as cancellations of large gatherings, had already been taken¹⁰, potentially lowering our R_0 estimate. While our R_0 estimate for Dhaka lies within the 90% highest density interval from a meta-analysis of pre-March 2020 estimates³⁴, it is lower than more recent estimates⁶³. The effect of lockdown on between-household transmission rates was, like R_0 , tuned to reported death data, and proved to be higher than was anticipated in this high density population; reducing by 97%, suggesting that lockdown was very effective as a short-term control measure. This high impact on compliant individuals might have been compensating for our conservative assumption of no reduction in transmission from essential workers under lockdown (unless off sick with symptomatic COVID-19), or underestimated lockdown compliance. An overestimated R_0 (or indeed inaccuracies in other parameters) could also lead to overestimated impacts of lockdown.

We demonstrated the sensitivity of outcomes to the timing and scale-up of interventions, but human behavioural responses most dramatically impact outcomes. For these reasons, our model was primarily developed as a means to understand the potentially synergistic impact of interventions, rather than to accurately forecast dynamics subject to unpredictable changing human behaviours. We therefore considered compliance to interventions to be a crucial interactive element

of our app to build understanding and guidance on policy. Within the app, we also modelled the degree to which the limited (but greatly increased) testing capacity would still under-detect circulating cases, given some degree of cognitive dissonance and the considerable uncertainty in pre- and asymptomatic transmission during the early months of the pandemic. Overall we found the interactive app to be effective for communicating epidemiological modelling outcomes to policymakers together with their caveats, and we recommend the use of such tools which can be tailored to other settings and interventions.

In summary, we found that two NPIs combined, masks and symptoms-based household quarantining, were capable of averting an anticipated public health crisis in Dhaka, while also being good value for money. These measures were rolled out in Bangladesh, and appear to have contributed to limiting transmission but the ensuing epidemic did stretch the health system. In practice, compliance with these interventions and fidelity of their implementation was highly heterogeneous, with measures relaxing over the year as activity returned to levels approaching normalcy. With cases surging in 2021, apparently driven by the B.1.35 variant, and with mass vaccination coverage very low, these interventions need renewed focus.

References

1. Li, Q. *et al.* Early Transmission Dynamics in Wuhan, China, of Novel Coronavirus–Infected Pneumonia. *N. Engl. J. Med.* **382**, 1199–1207 (2020).
2. European Centre for Disease Prevention and Control. COVID-19 situation update worldwide. (2021). Available at: <https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases>. (Accessed: 5th January 2021)
3. Cele, S. *et al.* Escape of SARS-CoV-2 501Y.V2 from neutralization by convalescent plasma. *Nature* (2021). doi:10.1038/s41586-021-03471-w
4. Planas, D. *et al.* Sensitivity of infectious SARS-CoV-2 B.1.1.7 and B.1.351 variants to neutralizing antibodies. *Nat. Med.* (2021). doi:10.1038/s41591-021-01318-5
5. Flaxman, S. *et al.* Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. *Nature* **584**, 257–261 (2020).
6. Amewu, S., Asante, S., Pauw, K. & Thurlow, J. The Economic Costs of COVID-19 in Sub-Saharan Africa: Insights from a Simulation Exercise for Ghana. *Eur. J. Dev. Res.* **32**, 1353–1378 (2020).
7. Andam, K. S., Edeh, H., Oboh, V., Pauw, K. & Thurlow, J. *Estimating the economic costs of COVID-19 in Nigeria. NSSP Working Paper 63* (2020). doi:10.2499/p15738coll2.133846
8. Gupta, M. *et al.* The need for COVID-19 research in low- and middle-income countries. *Glob. Heal. Res. Policy* **5**, 33 (2020).
9. Chowdhury, R. *et al.* Long-term strategies to control COVID-19 in low and middle-income countries: an options overview of community-based, non-pharmacological interventions. *Eur. J. Epidemiol.* **35**, 743–748 (2020).
10. Anwar, S., Nasrullah, M. & Hosen, M. J. COVID-19 and Bangladesh: Challenges and How to

Address Them. *Front. Public Heal.* **8**, 154 (2020).

11. Davies, N. G. *et al.* Age-dependent effects in the transmission and control of COVID-19 epidemics. *Nat. Med.* **26**, 1205–1211 (2020).
12. Ahmed, S. A. K. S. *et al.* Impact of the societal response to COVID-19 on access to healthcare for non-COVID-19 health issues in slum communities of Bangladesh, Kenya, Nigeria and Pakistan: results of pre-COVID and COVID-19 lockdown stakeholder engagements. *BMJ Glob. Heal.* **5**, e003042 (2020).
13. Truelove, S. *et al.* The potential impact of COVID-19 in refugee camps in Bangladesh and beyond: A modeling study. *PLOS Med.* **17**, e1003144 (2020).
14. Clark, A. *et al.* How many are at increased risk of severe COVID-19 disease? Rapid global, regional and national estimates for 2020. *medRxiv* (2020). doi:10.1101/2020.04.18.20064774
15. Lloyd-Sherlock, P., Ebrahim, S., Geffen, L. & McKee, M. Bearing the brunt of covid-19: older people in low and middle income countries. *BMJ* **368**, m1052 (2020).
16. United Nations, Department of Economic and Social Affairs, P. D. Database on Household Size and Composition 2019. (2019). Available at: <https://www.un.org/development/desa/pd/data/household-size-and-composition>. (Accessed: 11th January 2021)
17. Hodgins, S. & Saad, A. Will the Higher-Income Country Blueprint for COVID-19 Work in Low- and Lower Middle-Income Countries? *Glob. Heal. Sci. Pract.* **8**, 136–143 (2020).
18. Homaira, N., Islam, M. S., Hassan, Z., Haider, N. & Satter, S. M. Contact tracing for covid-19 in low- and middle-income countries. *BMJ Opin.* (2020).
19. Rahaman, K. R., Mahmud, S. & Mallick, B. Challenges of Testing COVID-19 Cases in Bangladesh. *Int. J. Environ. Res. Public Health* **17**, 6439 (2020).
20. Torres-Rueda, S., Sweeney, S., Bozzani, F. & Vassall, A. The health sector cost of different policy responses to COVID-19 in low- And middle- income countries. *medRxiv* (2020). doi:10.1101/2020.08.23.20180299
21. Pereira, M. *et al.* The need for fast-track, high-quality and low-cost studies about the role of the BCG vaccine in the fight against COVID-19. *Respir. Res.* **21**, 178 (2020).
22. Daniel D. Reidpath, Allotey, P., O'Brien-Malone, A. & Diamond, M. R. Re: Tackling covid-19: are the costs worth the benefits? COVID in (country) context. *BMJ* m1496 (2020). doi:10.1136/bmj.m1496
23. McBryde, E. S. *et al.* Role of modelling in COVID-19 policy development. *Paediatr. Respir. Rev.* **35**, 57–60 (2020).
24. Rahman, H. Z. *et al.* *Livelihoods, coping, and support during COVID-19 crisis. Power and Participation Research Centre (PPRC) & BRAC Institute for Governance and Development (BIGD)* (2020).
25. Yi, C. *et al.* Epidemiological characteristics of infection among close contacts of new coronavirus pneumonia in Ningbo City. *Chinese J. Endem.* **41**, (2020).
26. Liu, Y., Centre for Mathematical Modelling of Infectious Diseases nCoV Working Group, Funk, S. & Flasche, S. The contribution of pre-symptomatic infection to the transmission dynamics

- of COVID-2019. *Wellcome Open Res.* **5**, 58 (2020).
27. Byrne, A. W. *et al.* Inferred duration of infectious period of SARS-CoV-2: rapid scoping review and analysis of available evidence for asymptomatic and symptomatic COVID-19 cases. *medRxiv* (2020). doi:10.1101/2020.04.25.20079889
 28. Hu, Z. *et al.* Clinical characteristics of 24 asymptomatic infections with COVID-19 screened among close contacts in Nanjing, China. *Sci. China Life Sci.* **63**, 706–711 (2020).
 29. Linton, N. *et al.* Incubation Period and Other Epidemiological Characteristics of 2019 Novel Coronavirus Infections with Right Truncation: A Statistical Analysis of Publicly Available Case Data. *J. Clin. Med.* **9**, 538 (2020).
 30. Liang, W. *et al.* Clinical characteristics and outcomes of hospitalised patients with COVID-19 treated in Hubei (epicentre) and outside Hubei (non-epicentre): a nationwide analysis of China. *Eur. Respir. J.* **55**, 2000562 (2020).
 31. Verity, R. *et al.* Estimates of the severity of coronavirus disease 2019: a model-based analysis. *Lancet Infect. Dis.* **20**, 669–677 (2020).
 32. Rees, E. M. *et al.* COVID-19 length of hospital stay: a systematic review and data synthesis. *BMC Med.* **18**, 270 (2020).
 33. Halpin, S. J. *et al.* Postdischarge symptoms and rehabilitation needs in survivors of COVID-19 infection: A cross-sectional evaluation. *J. Med. Virol.* (2020). doi:10.1002/jmv.26368
 34. Davies, N. G. *et al.* Effects of non-pharmaceutical interventions on COVID-19 cases, deaths, and demand for hospital services in the UK: a modelling study. *Lancet Public Heal.* **5**, e375–e385 (2020).
 35. Keeling, M. J. *et al.* Predictions of COVID-19 dynamics in the UK: Short-term forecasting and analysis of potential exit strategies. *medRxiv* (2020). doi:10.1101/2020.05.10.20083683
 36. Bangladesh Bureau of Statistics. Bangladesh Population and Housing Census 2011. (2011). Available at: <http://203.112.218.65:8008/Census.aspx?MenuKey=43>.
 37. World Health Organisation (WHO). *Report of the WHO-China Joint Mission on Coronavirus Disease 2019 (COVID-19). The WHO-China Joint Mission on Coronavirus Disease 2019* (2020).
 38. United Nations, Department of Economic and Social Affairs, P. D. World Population Prospects 2019. (2019). Available at: <https://population.un.org/wpp/Download/Standard/Population/>. (Accessed: 17th September 2020)
 39. R Core Team. R: A language and environment for statistical computing. (2019).
 40. Soetaert, K., Petzoldt, T. & Setzer, R. W. Solving Differential Equations in R: Package deSolve. *J. Stat. Softw.* **33**, 1–25 (2010).
 41. Madewell, Z. J., Yang, Y., Longini, I. M., Halloran, M. E. & Dean, N. E. Household Transmission of SARS-CoV-2. *JAMA Netw. Open* **3**, e2031756 (2020).
 42. Bangladesh Bureau of Statistics. Household Income and Expenditure Survey (HIES). (2016).
 43. Howard, J. *et al.* Face Masks Against COVID-19: An Evidence Review. *Preprints* (2020). doi:10.20944/preprints202004.0203.v3

44. Stutt, R. O. J. H., Retkute, R., Bradley, M., Gilligan, C. A. & Colvin, J. A modelling framework to assess the likely effectiveness of facemasks in combination with 'lock-down' in managing the COVID-19 pandemic. *Proc. R. Soc. A Math. Phys. Eng. Sci.* **476**, 20200376 (2020).
45. Davies, A. *et al.* Testing the Efficacy of Homemade Masks: Would They Protect in an Influenza Pandemic? *Disaster Med. Public Health Prep.* **7**, 413–418 (2013).
46. Aydin, O. *et al.* Performance of fabrics for home-made masks against the spread of COVID-19 through droplets: A quantitative mechanistic study. *Extrem. Mech. Lett.* **40**, 100924 (2020).
47. European Centre for Disease Prevention and Control. Download today's data on the geographic distribution of COVID-19 cases worldwide. (2020).
48. Coronavirus COVID-19 Dashboard, 2020. (2020). Available at: <http://103.247.238.81/webportal/pages/covid19.php>. (Accessed: 19th November 2020)
49. Cowley, L. A. *et al.* Genomic and mobility data reveal mass population movement as a driver of SARS-CoV-2 dissemination and diversity in Bangladesh. *medRxiv* 2021.01.05.21249196 (2021). doi:10.1101/2021.01.05.21249196
50. World Health Organisation (WHO). Hospital beds (per 10 000 population). (2020). Available at: [https://www.who.int/data/gho/data/indicators/indicator-details/GHO/hospital-beds-\(per-10-000-population\)](https://www.who.int/data/gho/data/indicators/indicator-details/GHO/hospital-beds-(per-10-000-population)). (Accessed: 17th September 2020)
51. Aleta, A. *et al.* Modelling the impact of testing, contact tracing and household quarantine on second waves of COVID-19. *Nat. Hum. Behav.* **4**, 964–971 (2020).
52. Ferguson, N. M. *et al.* Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. (2020). doi:10.25561/77482
53. Wang, Y. *et al.* Reduction of secondary transmission of SARS-CoV-2 in households by face mask use, disinfection and social distancing: a cohort study in Beijing, China. *BMJ Glob. Heal.* **5**, e002794 (2020).
54. Hong, L. *et al.* Mask wearing in pre-symptomatic patients prevents SARS-CoV-2 transmission: An epidemiological analysis. *Travel Med. Infect. Dis.* **36**, 101803 (2020).
55. Bodas, M. & Peleg, K. Self-Isolation Compliance In The COVID-19 Era Influenced By Compensation: Findings From A Recent Survey In Israel. *Health Aff.* **39**, 936–941 (2020).
56. Ballard, M. *et al.* Prioritising the role of community health workers in the COVID-19 response. *BMJ Glob. Heal.* **5**, e002550 (2020).
57. Thunström, L., Newbold, S. C., Finnoff, D., Ashworth, M. & Shogren, J. F. The Benefits and Costs of Using Social Distancing to Flatten the Curve for COVID-19. *J. Benefit-Cost Anal.* **11**, 179–195 (2020).
58. Adam, D. C. *et al.* Clustering and superspreading potential of SARS-CoV-2 infections in Hong Kong. *Nat. Med.* **26**, 1714–1719 (2020).
59. Vespignani, A. *et al.* Modelling COVID-19. *Nat. Rev. Phys.* **2**, 279–281 (2020).
60. Iwasaki, A. What reinfections mean for COVID-19. *Lancet Infect. Dis.* **21**, 3–5 (2021).
61. Saha, S. *et al.* Detection of the B.1.1.7 and B.1.351 SARS-CoV-2 variants in Bangladesh. (2021). Available at: <https://virological.org/t/detection-of-the-b-1-1-7-and-b-1-351-sars-cov-2->

variants-in-bangladesh/668. (Accessed: 6th April 2021)

62. Brum, E. *et al.* Surging COVID-19 in Bangladesh driven by B.1.351 variant. *medRxiv* (2021).
63. Sanche, S. *et al.* High Contagiousness and Rapid Spread of Severe Acute Respiratory Syndrome Coronavirus 2. *Emerg. Infect. Dis.* **26**, 1470–1477 (2020).