COVID-19 Scientific Advisory Group
Rapid Evidence Report

Topic: COVID-19 Models, Scenarios and Thresholds

1. **Considering the various models that have been used internationally, information from past pandemics, and patterns in COVID-19 transmission in countries that have begun reducing public health restrictions, what are the most likely scenarios around COVID-19 transmission and case numbers in Alberta over the next 24 months (assuming no vaccine is available within that period)?**
2. **What indicators or thresholds are other provinces and health systems using, and is there evidence that these indicators or thresholds can reliably predict hospital and ICU use and demand on other resources (e.g., public health resources including contact tracing)?**

Context

- There are still several important unknowns about the COVID-19 virus (SARS-CoV-2), including how infectious asymptomatic case are, the presence and duration of immunity, and the role of seasonal attenuation.
- Models are an important tool to project the size of an unmitigated pandemic and the potential effect of various control measures on transmission dynamics and healthcare utilization.
- Transmission data from the most other pandemics suggests that the COVID-19 pandemic is likely to continue until 60% to 70% of the population is immune. This level of 'herd immunity' would optimally occur with the development and deployment of a COVID-19 vaccine, which is expected to take a minimum of 18-24 months.
- It is essential that decision makers within AHS understand the potential impact of different COVID-19 scenarios, and the evidence around what indicators or thresholds should prompt the escalation and de-escalation of services and public health controls as these decisions will have important implications on demand and delivery of health services (e.g., relaunching diagnostic services, surgical wait times).
- The review did not aim to examine the effectiveness, nor make recommendations, on the role of various public health interventions on the suppression of COVID-19.

*Note: When term "trigger" is used, it is meant to be interpreted as an indicator or threshold.

Key Messages from the Evidence Summary

- The accuracy of projection models, which are always a simplification of the problem, are constrained by our limited knowledge and experience with the SARS-CoV-2 virus and the parameters associated with its transmission. There are many sources of uncertainty and no standardized approach for calculating and reporting uncertainty in these models.
- Given model uncertainty, there is no consensus around future transmission patterns, case numbers and impact of the COVID-19 pandemic.
- Many studies predict the likely occurrence of at least a second wave of COVID-19 if not a more persistent pattern of recurrent resurgence that will continue until herd immunity is achieved (optimally through a vaccine).
- Only two studies at present were identified that examined the use of thresholds; however, both studies were designed to evaluate the use of thresholds in intensifying or relaxing public health interventions as

opposed to directly trying to predict cases and healthcare utilization. Little to no information about the reliability of the suggested thresholds was provided.
- Multi-pronged public health interventions (that can be cycled on/off) show the most promise in suppressing future waves of COVID-19 and preserving hospital resource capacity.
- Models suggest that measured approaches to the timing and cycling of public health interventions are required to appropriately balance the suppression of viral transmission and preserve capacity of the health care system to optimally manage COVID-19 surges as well and all other health care needs, and the need to stimulate and maintain economic activity.
- Indicators reportedly used in other jurisdictions (for example, population rates of incident COVID-19 cases) have not been assessed for reliability in predicting healthcare resource utilization.

Research Gaps

- Efforts should be made to strengthen the quality of the data being used for modelling, such as:
    - As relatively little is known about the virus and transmission dynamics, future modelling should focus on using real data (as local as possible) instead of literature-derived data on which to create model parameters and assumptions.
    - As more empirical data becomes available on effective contact rates, future modelling should more appropriately account for dispersion of SAR-CoV-2 (i.e., dynamic transmissibility to incorporate non-spreaders, super-spreaders, etc. vs static transmissibility between symptomatic / asymptomatic cases). Agent-based models can be used to model such transmission.
- Few studies included control measures such as usage of face masks when physical distancing cannot be maintained.

Committee Discussion

The committee members discussed at length the current state of evidence regarding potential scenarios for COVID-19 transmission over the next two years as well as the potential role of indicators, and thresholds within these indicators, to predict COVID-19 related outcomes including healthcare utilization (e.g., ICU beds). There was consensus that several important research gaps currently exist in this body of literature that preclude the committee from making any definitive recommendation around the most likely pattern for COVID-19 transmission over the next 18 to 24 months, though there was consensus among the committee that Alberta will continue to experience and need to plan for COVID-19 related activity and demands for the next 18 to 24 months. Further, the committee was in unanimous agreement to provide practical guidance to further guide decisions around planning for COVID-19 over the next 18 to 24 months, including guidance on the development of thresholds for supporting decision-making with the healthcare system. The committee supported use of a structured ethical framework to guide resource allocation in a resource-scarce scenario.

Practical Guidance

- SARS-CoV-2 transmission will likely come in waves of different intensity and intervals based on multiple factors, including the control measures in place. Modelling and planning for different scenarios will help ensure a healthcare system is prepared for various pandemic scenarios.
- Whatever scenario develops (assuming at least some level of ongoing mitigation), healthcare systems will most likely need to make provisions for at least another 18 to 24 months of potentially significant COVID-19 activity.
- Limited data from modeling studies suggest that cycling public health interventions on/off in response to a localized threshold may provide the best opportunity to suppress virus transmission and preserve system capacity.
- Selecting high versus low levels for thresholds will have important tradeoffs and impacts (i.e., on the frequency and duration of public health interventions and the broader impacts of these measures). Higher

thresholds could result in higher health care system demand and should only be used if the system has the capacity to meet such demand.

- There is intuitive logic to basing public health intervention thresholds on demand for healthcare utilization (e.g., ICU beds), as opposed to more indirect measures such as the number of new cases per 100,000 in the community (which is a metric used in a number of jurisdictions); however, none of the identified approaches are strongly supported by evidence or are clearly superior to one another.
- Especially relevant for Alberta, thresholds appear to be more adaptive when applied at a local level (e.g., municipality or zone) (versus provincial or national) and may lead to slightly shorter durations of time where public health interventions are in place.
- It will be challenging to predict the duration and intensity of individual COVID-19 surges, which will likely be cyclical in nature, and that their health system impact may be exacerbated within influenza season, so questions have arisen around planning for major initiatives with a significant operational impact (including ConnectCare implementation). Given health systems benefits to continued innovation, such work should be considered in the context of robust operational planning, building in contingency plans and flexibility to ensure the ability to alter or delay as necessary to deal with COVID-19. The risks and benefits must be carefully reviewed and constantly monitored approaching ConnectCare launches to enable “go” or “no go” decisions.

Strength of Evidence

This evidence review identified a number of studies of reasonable quality. The primary limitation to classifying model projections in these studies as ‘good’ quality is the current knowledge gaps around the SARS-CoV-2 virus. As a result, they require a considerable number of assumptions (e.g., how infectious asymptomatic cases are, role of seasonal attenuation, the presence and duration of immunity, etc.). There is also no standardized approach to assessing and reporting model calibration, which further complicates quality assessment.

Several of the models included in this review have received media attention; however, these models have been developed by jurisdictions or research groups without a supporting manuscript (preprint or otherwise). In addition, there is a large paucity of literature available on thresholds used to scale interventions up or down (only two studies were identified and those included provide little to no detail on the reliability of the suggested thresholds.

Limitations of this review

As this is a rapid review and evidence about SARS-CoV-2 is quickly and ever-changing, the included studies are not exhaustive of the emerging models. For feasibility of a rapid review, a targeted search strategy was applied to both the modelling and triggers questions. The search did not target the body of literature examining the role of public health interventions including the potential use of thresholds on COVID-19 outcomes using regression techniques (e.g., Cowling et al, 2020; Jüni et al, 2020). There is complexity around how terms such as “indicators”, “thresholds” or “triggers” are used in the literature, which could mean some studies were missed. However, variations of the selected search terms (including synonyms) were applied in trialing the search strategy with no increase in relevant returns. Finally, the available literature is often limited to studies not yet peer-reviewed (pre-print) or grey literature/jurisdictional reports.

Summary of Evidence

SARS-CoV-2, the virus that causes COVID-19, first emerged in Wuhan, China in December 2019, and its future course is highly unpredictable. Potential scenarios for the course of the pandemic over the next 12 to 24 months (Figure 1) exist in the literature but there remains high uncertainty and the trajectory of the virus is still unknown. Several authors have published models for predicting cases, deaths and healthcare utilization (HCU) (e.g., ICU and hospital beds and their associated resources) over various time periods. Although models can be an important predictive tool, all models are inherently wrong to an extent (Holmdahl and Buckee, 2020) as they depend on data quality and the confidence in model inputs. COVID-19 models are limited by current evidence around SARS-CoV-2 such as presence of immunity, infectiousness of asymptomatic cases, etc.

At this time there is considerable uncertainty around what the potential pandemic scenarios might be as many jurisdictions are just beginning to move beyond the initial peak, especially given there are that some countries with lifted restrictions are beginning to see another rise in cases (Worldometer, 2020). Several groups have suggested patterns of future surges or waves of COVID-19. For example, the University of Minnesota (CIDRAP, 2020) have proposed three possible scenarios from January 2020 to January 2022 (Figure 1):

Scenario 1: Waves of SARS-CoV-2 that mirror peaks and valleys, with the initial wave of the virus running through spring 2020, followed by a series of smaller waves over the summer and continuing for 12 to 24 months.

Scenario 2: A fall peak scenario, in which a second, larger wave of the virus emerges in fall or winter 2020 (after the initial wave in spring 2020), followed by smaller waves in 2021.

Scenario 3: A 'slow burn' pattern of ongoing transmission of SARS-CoV-2 following the initial spring 2020 wave, with no clear pattern to subsequent smaller waves.

Similarly, Grube and Patel (2020) hypothesize four scenarios for COVID-19 hospital cases over the next 12 months (Figure 2). These include: optimistic (Quick Recovery) and pessimistic (Long Slog) scenarios; a secondary wave scenario (Secondary Surge); and new normal (Seasonal Surges). Clearly, the ability to determine which scenario is most likely will be critical for ongoing management of the pandemic.

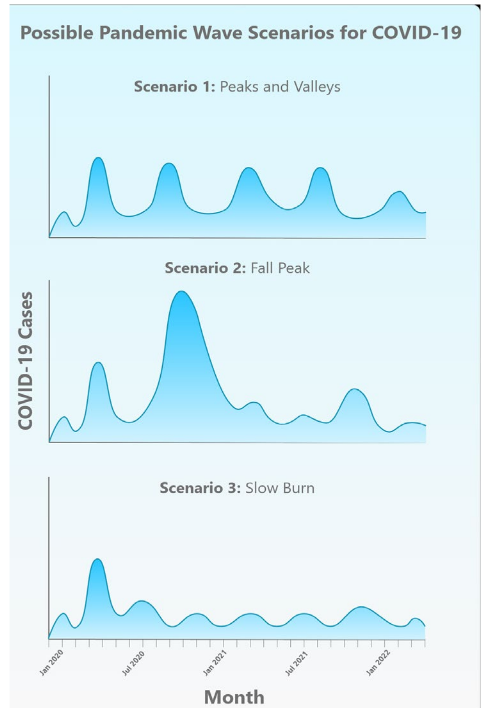

Figure 1. Potential wave scenarios for COVID-19 (from: CIDRAP, 2020)

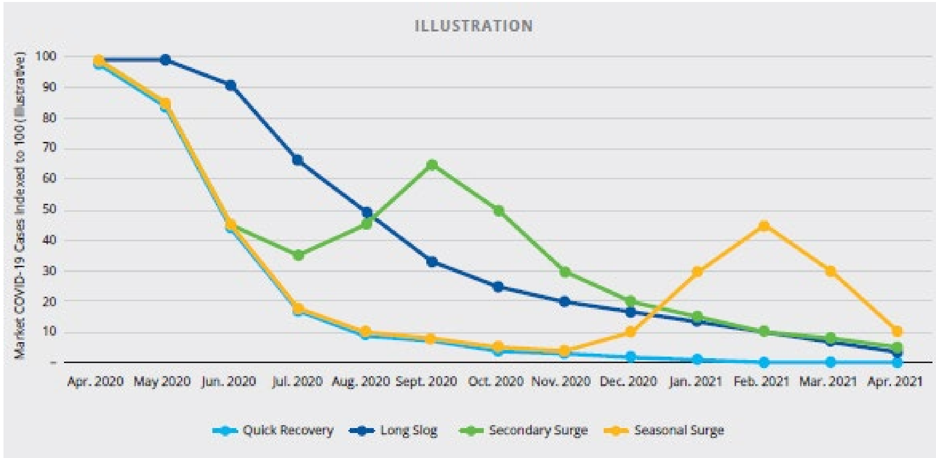

Figure 2. Potential wave scenarios for COVID-19 (from: Grube and Patel, 2020)

With all the unknowns related to the future of COVID-19, it is no surprise that there are a variety of modelling approaches and parameters being used (e.g., Ferguson et al, 2020; Kerr et al, 2020; Kissler et al, 2020; Tuite et al, 2020; Zhana et al, 2020), making it challenging to compare model output and determine which model or scenario is likely to be the most accurate. A key constraint is that the *true* number of COVID-19 infections to date is unknown and thus leads to a high level of uncertainty in the models. Using confirmed cases when modelling results in a spatially heterogeneous fraction of the true number of cases. As such, modelling based on hospitalization and deaths (albeit still a fraction of the true number of cases) may be a more reliable data source and input. Nonetheless, all models still require many assumptions given how poorly understood the virus is at this time (Holmdahl and Buckee, 2020). For example, it is currently unknown whether immunity exists and if so the extent to which immunity for SARS-CoV-2 will last (longer immunity leads to lower risk of recurrent outbreaks), the extent to which asymptomatic cases transmit SARS-CoV-2, and what immunity would look like in the COVID-19 population.

Another important limitation is that there is currently no standardized approach to calculating and reporting uncertainty in models, and many challenges exist to accurately model contact rates for those infected or susceptible to SARS-CoV-2 under various scenarios (i.e., with strict public health control measures in place and as countries begin to reduce these restrictions and reopen). No model is perfect and all are limited by what is known and what is assumed; however, understanding model limitations and using them appropriately can provide guidance regarding the potential trajectory of the pandemic (Holmdahl and Buckee, 2020). This rapid review provides a preliminary, targeted search of the literature: however, further investigation will be required to evaluate the statistical approaches used in constructing these models. It is important to note that the primary aim of this review was not to examine the effectiveness, nor make recommendations, on the role of various public health interventions (or non-pharmaceutical interventions [NPIs] [McCoy et al, 2020]) on the suppression of COVID-19; however, modelling studies that included scenarios of different combinations of public health interventions were examined with the aim of identifying prominent scenarios for SARS-CoV-2 transmission over the next 24 months and potential thresholds that may inform ongoing planning within the healthcare system.

Research Question 1:

Considering the various models that have been used internationally, information from past pandemics, and patterns in COVID-19 transmission in countries that have begun reducing public health restrictions, *what are the most likely scenarios around COVID-19 transmission and case numbers in Alberta over the next two years (assuming no vaccine is available within that period)?*

Evidence from the primary and grey literature

To better understand transmission dynamics and impending case counts of the COVID-19 pandemic over the coming years, several authors have used various modelling approaches to evaluate potential scenarios. **Table 1** provides an overview of select modelling studies for COVID-19. As this is a rapid review, Table 1 is by no means an exhaustive list of all of the modelling studies emerging as the world tries to understand potential pandemic scenarios. The selected models are those that (i) take into account some level of public health interventions (e.g., contact tracing, quarantine, physical distancing, school and workplace closures) and (ii) provide model projections for number of COVID-19 cases, deaths and/or HCU over the next few months to the next five years. The following sections highlight the types of models selected and their projections across three outcomes of interest (i.e., case numbers, deaths, HCU).

Modelling Cases and HCU

Aleta and colleagues (2020) used a synthetic population of the Boston Metropolitan Area to develop a data-driven, agent-based model of SARS-CoV-2. Their goal was to model transmission dynamics of the pandemic while evaluating the impact of social distancing interventions. The authors summarize three scenarios: (i) an unmitigated scenario, (ii) a 'LIFT' scenario (in which a stay-at-home order is lifted after eight weeks except for mass gatherings), and (iii) a 'LET' scenario (in which a stay-at-home order is lifted after eight weeks with enhanced tracing in place) and report the peak incidence of newly infected individuals as well as normal and ICU hospitalizations. The authors found that in all LIFT scenarios, the second wave of the pandemic would still have potential to overwhelm the healthcare system. Therefore, they recommend the LET scenario as the optimal strategy as it allows relaxation of social distancing interventions while maintaining hospital and ICU demand at manageable levels. This study suggests that lifting public health interventions such as social distancing will require a robust system for contact tracing and quarantine to ensure a second wave does not overwhelm the healthcare system.

Davies et al. (2020), used a stochastic, age-structured transmission model to explore a range of intervention scenarios, including introduction of school closures, social distancing, shielding of elderly groups, self-isolation of symptomatic cases, and extreme lockdown-type restrictions. The authors simulated different durations for these interventions and triggers for their introduction as well as combinations of interventions. Various scenarios were modelled and projections included estimated new cases over time, number of patients requiring inpatient treatment and critical care (intensive care unit [ICU]), and deaths. The authors found that no single interventions (including school closures, social distancing, elderly shielding or self-isolation) would effectively impact R_0 enough to lead to the required decline in total case numbers. As indicated, the authors also evaluated the potential impact of combining multiple public health interventions and found the most comprehensive scenario (i.e., deploying all four interventions simultaneously) resulted in the largest impact on decreasing R_0; however, it was only sufficient to halt the epidemic altogether in a small proportion of simulations. The authors concluded that a scenario in which more intense lockdown measures were implemented for shorter periods may be able to keep projected case numbers at a level that would not overwhelm the health system.

Kissler and colleagues (2F020) used a two-strain ordinary differential equation (ODE) susceptible-exposed-infection-recovered (SEIR) compartmental model and the transmission dynamics of HCoV-OC42 and HCoV-HKU1 (the second-most common causes of the 'common cold') to model the potential dynamics of SARS-CoV-2 until 2025. The model accounted for seasonality, immunity, and cross-over immunity with HCoV-OC42 and HCoV-HKU1 and included categories of possible SARS-CoV-2 seasonal patterns (i.e., annual outbreaks, biennial outbreaks, sporadic outbreaks or virtual elimination). The authors report four key points regarding model simulations for potential SARS-CoV-2 transmission: 1) proliferation at any time of the year, 2) regular circulation as immunity isn't permanent, 3) seasonal variation, and 4) virus elimination for five or more years. The authors suggest that not exceeding critical care capacity is a key metric to ensure the successful impact of social distancing measures. As such, one-time social distancing interventions were evaluated at implementation durations of 4 weeks, 8 weeks, 12 weeks, 20 weeks, and indefinitely, with and without forcing seasonal variation. All scenarios resulted in a resurgence of the virus once social distancing was lifted. Importantly, longer periods of social distancing did not always correlate with larger reductions to pandemic peak side. For example, a 60% reduction in R_0 for a 20-week social distancing simulation resulted in a recurrence peak similar to the size of the uncontrolled pandemic. More importantly, the models that forced seasonal variation produced resurgence peaks that could be larger than that of the unconstrained pandemic peak in terms of total number of infected and peak prevalence. With respect to maintaining critical care capacity, the one-time interventions were not effective at maintaining the prevalence of critical care cases below capacity. The authors suggest that to avoid exceeding critical care capacity, cycling social distancing measures on/off may be required into 2022.

Barbarossa et al. (2020) used a SEIR model to predict spread of COVID-19 and evaluate the impact of non-pharmaceutical interventions (NPIs [e.g., social distancing, contact tracing]) in Germany until January 2021. The authors simulated five scenarios: (i) no NPI intervention; (ii) adoption of main control measures (e.g., remote working, closure of schools); (iii) enriched baseline measures with increased testing; (iv) partial lifting of current restrictions; and (v) near-total shutdown of economic/social activities for five weeks. Findings indicate that NPI interventions with increased testing would likely reduce COVID-19 infections by at least 60% and reduce fatalities. However, these scenarios would also likely slow the number of recovered and immune by preventing transmission. Further, model output indicated that a partial lifting of restrictions would result in (i) an approximately 15% increase in death toll compared to the baseline scenario and (ii) second epidemic with longer duration (i.e., more than one year). Lastly, the authors observed that a total shutdown in Germany could still lead to approximately 570,000 fatalities into 2021, and the primary effect of a shutdown with abrupt start and end is the delay of a known active case peak. In conclusion, the authors suggest that combining NPIs provides the most effective approach to limit the severity of COVID-19.

Modelling HCU and Death

Perkins and Espana (2020) used a mathematical model to depict a range of likely control measures and their potential consequences in relation to COVID-19 transmission. Specifically, the authors employed an ‘optimal control theory’ to gauge optimal strategies for implementing NPIs to control the spread of COVID-19. Model data was calibrated using US data to simulate projections from May 2020 to December 2021. Two scenarios were simulated to examine the effects of NPIs on COVID-19 transmission: (i) optimal level of NPI control and (ii) optimal control with delays in initiating NPIs. The authors found that under an optimal control scenario, hospitalizations would remain low through 2021. In contrast, lower levels of NPI control were projected to lead to rapid increases in hospitalizations and the occurrence of a second wave of the pandemic in summer 2020 with hospital capacity at 20-fold and cumulative deaths equaling 5% of the national population. Model scenarios that employed NPI control at varying timeframes indicated that delays in control would result in higher incidence of infection, leading to higher levels of subsequent transmission, higher depletion of susceptible population and less need for control later on. Further, cumulative deaths through 2020 and 2021 decreased with earlier control implementation and increased when controls began later. The authors suggest the findings of this study demonstrate that extended NPI control should be applied to circumvent COVID-19 resurgence in the forthcoming months, avoiding incidence rates that would exceed health system capacity.

Keeling et al. (2020) used a deterministic, age-structured transmission model to predict the effects of relaxing social distancing measures and simulate up-to-date epidemic spread projections from May 2020 to July 2021. The authors simulated four scenarios based on (i) current lockdown measures, (ii) age-independent relaxation of lockdown measures, (iii) age-dependent relaxation of lockdown measures and (iv) full lockdown relaxation via region-based reintroduction strategies. Results from the modelled scenarios suggest that under current lockdown measures, England and Wales will be most severely affected with the highest number of deaths per capita, with Scotland and Northern Ireland seeing lower number of deaths per capita. Further, the authors observed how age factors into relaxation of lockdown measures. For the age-independent scenario, model predictions indicate a likely case resurgence in late June, but in the long-term, hospital and ICU demand would remain within capacity. In comparison, an age-dependent lockdown scenario for those over 65 years old would minimize the total number of deaths, but have marginal overall impact. The authors suggest that strict lockdown measures only for older age groups could put severe demands on the health system with a potential second-wave among younger adults. Finally, relaxing lockdown measures at a regional-level could lead to a second, smaller peak in May. However, the model predicted that cases would gradually reduce over time, with the epidemic hitting low levels in late 2020 and remaining stable to the latter half of 2021. Concluding evidence from this study demonstrates a need for cautious relaxation of current lockdown measures to protect health care systems and vulnerable groups.

Modelling HCU only

Tuite and colleagues (2020a) used an age-structured compartmental transmission dynamic model of COVID-19 to explore the potential impact of various NPIs (e.g., contact tracing, quarantine, physical distancing, hand hygiene) on the number of severe cases (i.e., hospital and ICU admissions) in Ontario, Canada over a two-year timeframe. The authors concluded that dynamic interventions (i.e., those that turn on/off based on the number of cases requiring ICU care) were the most effective at reducing the proportion of the Ontario population infected by COVID-19 while also requiring shorter periods of social distancing. Dynamic interventions of restrictive social distancing, or enhanced capacity for testing and contact tracing with less restrictive social distancing measures, were the only scenarios found to reduce the median number of ICU cases below Ontario's current ICU capacity. As such, dynamic NPIs provide an optimal strategy to slow COVID-19 cases from overwhelming ICU capacity. In a letter published in Annals of Internal Medicine, Tuite et al. (2020b) calibrated the model to reflect most recent data and revised model parameters. The authors report that in this updated model, lifting restrictions after eight weeks from 70% of normal social contact to 50% contact would result in ICU capacity being exceeded within 55 days of the lifted restrictions, whereas capacity would not be exceeded if the restrictions remain in place at 70% of normal contact.

Table 2 highlights additional influential and highly cited COVID-19 modelling studies that have been developed over the past few months. These models only give short-term projections and therefore were not considered primary evidence to answering the research question; however, a lot can be learned about the utility of modelling when examining the accuracy of model projections for which the projected timeframe has passed. Further, several organizations have produced interactive dashboards that model ongoing projections for several key measures including estimated infections, confirmed infections, total deaths, daily deaths, bed availability, ICU bed availability, and invasive ventilator needs (IHME, 2020; Los Alamos, 2020). These can be useful as long-term projections are challenging to rely on in situations such as COVID-19 with the high level of uncertainty that currently existing around what is known about the virus.

The Los Alamos National Laboratory's (2020) COVID-19 case data model forecasts the number of future confirmed cases and deaths using data from John Hopkins University (JHU) Coronavirus Resource Center dashboard for all US states and Global jurisdictions. The model (i) estimates changes in the number of COVID-19 infections over time; and (ii) compares the number of infections to the reported data. It is calibrated to allow for short- (i.e., one week) and longer-term (i.e., six weeks) projections with updated data on Mondays and Thursdays. This model can be filtered and applied to a Canadian context and is updated regularly as new data becomes available through its online interactive tool. Using the tool to examine short- and long-term forecasts for Canada, it is estimated that in the past week (2020-05-20), the total number of confirmed cases has been increasing by an average of 1.5% per day and the total number of deaths has been increasing by an average of 1.8% per day. Further, by July 1, the model forecasts approximately 111,000 total confirmed cases (90% Prediction Interval: 94,400 - 152,000) and 9,200 total deaths (90% Prediction Interval: 7,500 - 13,400). Additionally, based on data as of May 20, the largest single-day increase in confirmed cases occurred on April 5 with 2,778 cases, and therefore there is a ~96% chance that the peak (i.e., the maximum number of new daily confirmed cases) has occurred in Canada. Several limitations are associated with this model. For example: (i) confirmed cases and deaths are underestimates for actual case counts; (ii) the model forecasts and does not project, indicating that it does not explicitly model intervention effects or hypothetical scenarios; and (iii) variable testing capacity, intervention measures and case definitions may yield inexact forecasts.

Yamana et al. (2020) modelled two types of movement - daily work commuting and random movement - to forecast the effects of weekly transmissibility increases in relation to the effective reproduction number R_t on COVID-19 outcomes in the United States over a six-week period. An age-stratified infection fatality rate was used to simulate infections to death. Projections were generated using a county-scale metapopulation model optimized to daily confirmed cases and deaths from February 21 to May 2, 2020. This model simulated three scenarios: (i) applying a weekly 20% decrease in transmissibility first with a one-time 10% increase in states with return-to-work orders, (ii) applying a weekly 10% increase in states with return-to-work orders, and (iii) applying a baseline 20% decrease in states with growing weekly cases. Results indicated that a one-time 10% increase in transmissibility would likely result in a rebound of COVID-19 incidence, and reopening states could experience exponential growth of both cases and deaths. The authors observed a faster and stronger rebound of COVID-19 in the second scenario with a weekly 10% increase in transmissibility, and lastly, a sustained 20% weekly decrease in transmissibility projects exponential growth of both cases and deaths in reopening states, and decreasing or stable numbers of cases and deaths in states with sustained restrictions. However, increases in the number of COVID-19 cases and deaths are likely to not be apparent at the national-level until 2-4 weeks after first states begin to reopen. As well, the application of this model is variable to local context (i.e., contact behaviour, population density, control measures, testing practices). In conclusion, this model's results suggest an estimated rebound in COVID-19 prevalence and deaths 2-4 weeks post-opening, with variability according to the three simulated scenarios based on different levels of individuals' contact and movement.

Conclusion

In summary, many studies project the likely occurrence of a second wave of COVID-19 and possibly a more persistent pattern of resurgence; however, the specifics, duration and frequency of subsequent waves is a topic of considerable debate in the current literature (Aleta et al., 2020; Kissler et al., 2020; Perkins and Espana, 2020). This lack of clarity is due in part to the fact that no countries have experienced a second surge at this time as it is still too early in the pandemic. Given the inability of models to converge on a likely projection for a future pattern of the pandemic it will be prudent to employ a reactive and measured approach, including the use of thresholds, to be best positioned to appropriately implement and ease public health interventions and successfully balance viral suppression with economic stimulation (Tuite et al., 2020; Keeling et al., 2020). Several authors agreed that multi-pronged public health interventions (e.g., physical distancing, contact tracing) that can be cycled on/off provide an optimal scenario for suppressing COVID-19 cases while also keeping healthcare utilization within capacity (Aleta et al, 2020; Barbarossa et al., 2020; Hellewell et al., 2020; Tuite et al., 2020). Across the included studies it is not possible to identify common key assumptions to inform the future pattern, duration and intensity of the pandemic. Having said that, there do appear to be commonly accepted public health interventions that appear most effective on mitigating the spread of COVID-19 (and thereby managing healthcare utilization) within the various modelling papers, including social distancing, testing, case isolation and contact tracing (Aleta et al, 2020; Barbarossa et al, 2020; Chowdhury et al, 2020; Davies et al, 2020; Perkins and Espana, 2020; Tuite et al, 2020).

Research Question 2

What indicators or thresholds are other provinces and health systems using, and is there evidence that these indicators or thresholds can reliably predict hospital and ICU use and demand on other resources (e.g., public health resources including contact tracing)?

As countries around the world move into plan for phased relaunches of economies (Gottlieb et al., 2020; Prime Minister of Canada, 2020), the transmission pattern and impact of COVID-19 on long-term case numbers, deaths and other aspects of healthcare utilization (HCU) (e.g., ICU beds and associated resources) remains unknown. In response to this uncertainty, modelling studies have explored the potential of various public health interventions (e.g., social distancing) to limit transmission and reduce HCU. These studies provide some insight into how different combinations of interventions (many of which can be cycled on/off in response to a measured trigger) can impact transmission dynamics and HCU and thus support decision making. As with all models, the accuracy of findings is highly dependent on model inputs and assumptions, including the efficacy of interventions, and there are many limitations to current modelling studies for COVID-19 (see Research Question 1). Evidence suggests that healthcare systems consider the timing and level (i.e., national versus local) of selected indicators or thresholds (referred to as "triggers" in included studies) as these decisions will have implications for transmission patterns, HCU as well as broader socio-economic impacts.

Evidence from the primary literature

Table 3 summarizes two key studies on COVID-19: (i) a report from the Imperial College COVID-19 Response Team (Ferguson et al., 2020) and (ii) a pre-print from Davies et al. (2020). Both studies provide relevant, good quality information on the use of thresholds to cycle public health interventions on/off in an effort to reduce virus transmission and maintain hospital resource capacity. They also both identify important considerations for the threshold (high versus low) and level (local versus national) of these types of thresholds that may be useful for ongoing pandemic management and planning. These studies both have limitations (see below), including a paucity of information on the quality of the predictions within their models. As such, their findings must be interpreted with the same caution required for all modelling studies.

It is worth noting that these were the only two studies that fit the pre-determined inclusion/exclusion criteria for this rapid review. This demonstrates that the body of evidence is currently limited regarding the selection and use of thresholds for accurately predicting viral dynamics for COVID-19, cases and demand on system capacity.

Ferguson et al. (2020) modified an individual-based simulation model to assess the potential role of various public health measures (i.e., NPIs) aimed at reducing contact rates in the population and COVID-19 transmission. The authors modelled the impact of different mitigation and suppression strategies on the total number of deaths and peak demand for ICU beds over a two-year period. They concluded that suppression strategies are the more effective approach as mitigation strategies were unable to prevent overwhelming the healthcare systems. In fact, combining all four interventions (social distancing of the entire population, case isolation, household quarantine, and school and university closures) was shown to be most effective at reducing both ICU peak demand and total deaths. The authors also explored various thresholds for triggering on/off cycles of interventions. They considered scenarios where interventions were only initiated after weekly confirmed case incidence in ICU patients (a group of patients highly likely to be tested) exceeded a certain "on" threshold, and relaxed when ICU case incidence fell below the "off" threshold. Various combinations of NPIs were modelled and the authors found that lower thresholds for "on" triggers resulted in lower demands on peak ICU beds and total deaths. Total deaths were also reduced with lower "off" triggers, but peak ICU demand and the proportion of time social distancing is in place were not affected by the threshold for the "off" trigger. Finally, in agreement with Davies et al. (2020), these authors also conclude that local triggers are more adaptive than national triggers lead to slightly shorter durations of time where NPIs are in place.

Davies et al. (2020) used a stochastic, age-structured transmission model to explore a range of intervention scenarios, including introduction of school closures, social distancing, shielding of elderly groups, self-isolation of symptomatic cases, and extreme lockdown-type restrictions. The authors simulated different durations of interventions and triggers for introduction, as well as combinations of interventions. Various scenarios were modelled and projections included estimated new cases over time, number of patients requiring inpatient treatment and ICU care, and deaths. The authors found that a scenario in which more intense lockdown measures were implemented for shorter periods may be able to keep projected case numbers at a level that would not overwhelm the health system. Further, to minimize total health burden, it was advantageous to trigger interventions later in the epidemic. The authors also examined whether the threshold for the trigger should be high (e.g., 5,000 ICU bed capacity) or low (e.g., 1,000 ICU bed capacity) and found differential impacts on the frequency and duration of lockdown periods. More specifically, higher thresholds resulted in more frequent, but shorter lockdowns, compared to lower thresholds that resulted in less frequent but longer lockdown periods. Also of importance, higher thresholds resulted in higher peak demands on ICU bed capacity and lower thresholds resulted in more individuals remaining susceptible at the end of the simulation period, potentially increasing the total duration for which recurrent lockdowns would need to be maintained, as well as the potential impact on quality of life and the economy. The authors also concluded that triggering interventions locally instead of nationally could modestly reduce the total number of cases and deaths, as well as reduce peak demands on the healthcare system. This latter point is especially relevant for Alberta, where there has been significant regional variation in the burden of COVID-19.

Evidence from secondary and grey literature

Table 4 summarizes a variety of reports, news articles and commentaries regarding the types of metrics, indicators and information being used to gauge the ongoing transmission of COVID-19 and support the planning and decision-making of several jurisdictions across the world. While most of these sources do not include well-defined thresholds, nor do they offer details around associated models and predictions, they do provide important context for understanding how other jurisdictions are approaching the ongoing, dynamic management and planning for the relaunch of economies and healthcare services. Multiple jurisdictions are using new COVID-19 case counts as a threshold to indicate that hospital capacity verges on being overwhelmed and action must be taken (i.e., reinstate public health interventions). Specifically:

- Four jurisdictions use a specific threshold of 30 to 50 new cases per 100,000 per week as a predictor of hospital capacity.
- In contrast, Ontario suggests a much lower threshold of 200 new cases per *day*. (Note: 50 new cases per 100,000 per *week* roughly translates into 1,043 cases per day for Ontario and is based on the capacity of the system to do contact tracing [Government of Pennsylvania, 2020; Rau et al, 2020; Tagesschau, 2020]).
- Some reports describe what the threshold is trying to broadly predict but none comment on the reliability of the selected thresholds.

Other commonly cited measures to gauge COVID-19 pressures (without a direct link to what outcomes are being predicted) include (i) COVID-19 hospitalizations, (ii) number of long-term care home outbreaks, (iii) in-hospital outbreaks and (iv) hospital testing capacity and turn-around time. Commonly cited measures to gauge system capacity included bed capacity and PPE supply.

In summary, for Research Question 2, the included studies modelled the impact of different combinations of public health interventions on numerous COVID-19 outcomes (e.g., cases, deaths, ICU capacity) and examined the use of various thresholds to cycle public health interventions on/off, with one paper commenting on the trade-offs between selecting a high versus low threshold; however, neither study commented on the reliability of using thresholds for predicting COVID-19 outcomes (e.g., cases, deaths, ICU capacity). Since a key goal of measures to slow or prevent transmission of COVID-19 is to prevent the health system from being overwhelmed, there is intuitive logic to basing thresholds on demand for ICU beds (i.e. the approach of Ferguson et al.) with or without other measures of acute care utilization such as demand for hospital beds, as opposed to more indirect measures such as the number of new cases. However, none of the identified approaches are strongly supported by evidence or are clearly superior to one another.

Evolving Evidence

The evidence for these research questions is rapidly evolving. This review will be updated as new data from additional trials and studies is available. It will be important to be able to assess the quality and outcomes of new modelling studies as they become available, including a critical examination of the statistical approaches applied to model development, calibration and validation.

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Authorship and Committee Members

This review was written by Jamie Boyd with assistance from Amanda Davis, and scientifically reviewed by Melissa Potestio (primary reviewer), Laura McDougall, David Strong, Jason Cabaj, Tyler Williamson and Marcello Tonelli. The full Scientific Advisory Group was involved in discussion and revision of the document: Braden Manns (co-chair), Lynora Saxinger (co-chair), John Conly, Alexander Doroshenko, Shelley Duggan, Elizabeth MacKay, Andrew McRae, Nelson Lee, Jeremy Slobodan, James Talbot, Brandie Walker, and Nathan Zelyas.

Table 1. Modelling Studies Projecting COVID-19 Cases, Healthcare Utilization and Death

Reference			*Jurisdiction*
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/ Scenarios**	**Results**
Limitations			
Conclusion			
Reference: Aleta, A., Martin-Corral, D., y Piontti, A. P, et al. Modeling the impact of social distancing, testing, contact tracing and household quarantine on second-wave scenarios of the COVID-19 epidemic. medRxiv.2020. https://www.medrxiv.org/content/10.1101/2020.05.06.20092841v1.full			*Jurisdiction*: Boston Metropolitan Area
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/ Scenarios**	**Results**
Through the integration of anonymized and privacy-enhanced data from mobile devices and census data, the authors build a detailed sample of the synthetic population of the Boston metropolitan area in the United States. This synthetic population is used to define a data-driven agent-based model of SARS-CoV-2 transmission and to provide a quantitative analysis of the evolution of the epidemic and the effectiveness of social distancing interventions. Timeline: Models transmission dynamics out till December 2020.	Authors implemented a stochastic, discrete-time compartmental model in which individual transition from one state to the other according to key time-to-event intervals (e.g., incubation period, serial interval, and time from symptom onset to hospital admission) as from available data on SARS-CoV-2 transmission. Individuals were assigned based on age group. Assumptions - Assumes a basic reproductive number R_0 = 2:5, which together with the rest of the parameters yields a generation time Tg = 6:6 days. - A 25% fraction of asymptomatic individuals. Parameters: latent period, proportion of asymptomatic, pre-symptomatic period, time to removed/home stay, symptomatic case hospitalization ratio (%), ICU % among hospitalized, days from home stay to hospital admission, days in hospital, days in ICU, proportion of pre-symptomatic transmission, transmission from symptomatic to asymptomatic individuals,	Unmitigated scenario	- Mean and 95% C.I. of the number of normal hospitalizations 4.57 (4.10-5.03), ICU hospitalizations 2.56 (2.21-2.91) at the peak of the epidemic per 1,000 people. - Unmitigated epidemic would have a peak incidence of 25.2 (95% C.I: 23.8-26.4) newly infected individuals per 1,000 people. The epidemic follows a typical trajectory, namely, when the effective reproduction number Rt as a function of time becomes smaller than 1, the transmission dynamics slows down and eventually vanishes after having infected about 75% of the population. At the peak of the unmitigated epidemic, the number of ICU beds needed exceeds by far the available capacity (dashed horizontal line in Figure 3a) by more than a factor of 12, thus indicating that the health care system would suffer large service disruptions, resulting in additional deaths due to hospitals overcrowded with patients with COVID-19
		Lift scenario (LIFT): the “stay at home” order is lifted after 8 weeks by re-opening all work and community places, except for mass-gathering locations such as restaurants, theaters, and similar	- Mean and 95% C.I. of the number of normal hospitalizations 3.22 (2.80-3.67), ICU hospitalizations 1.87 (1.55-2.20) at the peak of the epidemic per 1,000 people.

	transmission for pre-symptomatic individuals Simulated social distancing strategies: - School closures simulated by removing all schools from system simultaneously - Partial 'stay at home' – assumes all places are open except restaurants, nightlife, cultural places; simulated closures of these places by removing all interactions in any place that falls into category according to Foursquare taxonomy of places. This situation occurs after first reopening scenario - Full 'lockdown and confinement' – mainly schools, all non-essential workplaces closed; in this simulation, all workplaces except essential are closed and interactions are removed. Essential workplaces are: hospitals, salons, barbers, grocery stores, dispensaries, supermarkets, pet stores, pharmacies, urgent care centers, dry cleaners, drugstores, maternity clinics, medical supplies, gas stations	locations (see SM). Assume that symptomatic COVID-19 cases are isolated within 2.5 days. The latter partial re-opening is enforced for another 4 weeks, which is followed by a full lifting of all the restrictions that remained. We consider that schools will remain closed given the impending summer break in July and August, 2020.	- Numerical results show that the LIFT scenario, while able to temporally abate the epidemic incidence, does not prevent the resurgence of the epidemic and a second COVID-19 wave when the social distancing measures are relaxed. - Following the lifting of social distancing the infection incidence starts to increase again, and the effective reproductive number, that dropped by circa 75% and reached values below 1 with the intervention, increases to values up to 2.05 (95%CI: 1.73-2.47). Indeed, at the time of lifting the social distancing intervention the population has not achieved the level of herd immunity that would protect it from the resurgence of the epidemic. Second wave of the epidemic still has the potential to infect a large fraction of the population and to overwhelm the health care systems. The number of ICU beds needed, although half the unmitigated scenario, is still exceeding by far the estimated availability. Such scenario would imply resorting again to major distancing policies, as it would be untenable to let run the epidemic again. This suggests that lifting social distancing without the support of additional containment strategies is not a viable option.
		Lift and enhanced tracing (LET) scenario: The "stay at home" order is lifted as in the previous scenario. Once partial reopening is implemented, authors assume that 50% of symptomatic COVID-19 cases can be tested for SARS-CoV-2 infection, on average, within 2 days after onset of	**LET Detection 30%** - No tracing: Mean and 95% C.I. of the number of normal hospitalizations 2.70 (2.29-3.12), ICU hospitalizations 1.58 (1.27-1.88) at the peak of the epidemic per 1,000 people.

		symptoms and that they are isolated at home and their household members are quarantined successfully for 2 weeks (a sensitivity analysis for lower rate of isolation and quarantine is presented in the SM). Also assume that a fraction of the non-household contacts (results for 20% and 40%) of the symptomatic infections can be traced and quarantined along with their household as well. Note that authors consider that the contact tracing is more likely to pick up interactions proportionally to the time spent together.	- Tracing 20%: Mean and 95% C.I. of the number of normal hospitalizations 0.86 (0.65-1.10), ICU hospitalizations 0.55 (0.39-0.72) at the peak of the epidemic per 1,000 people. - Tracing 60%: Mean and 95% C.I. of the number of normal hospitalizations 0.35 (0.21-0.50), ICU hospitalizations 0.22 (0.12-0.34) at the peak of the epidemic per 1,000 people. **LET Detection 50%** - No tracing: Mean and 95% C.I. of the number of normal hospitalizations 2.35 (1.97-2.75), ICU hospitalizations 1.39 (1.11-1.68) at the peak of the epidemic per 1,000 people. - Tracing 20%: Mean and 95% C.I. of the number of normal hospitalizations 0.44 (0.28-0.62), ICU hospitalizations 0.28 (0.16-0.42) at the peak of the epidemic per 1,000 people. - Tracing 60%: Mean and 95% C.I. of the number of normal hospitalizations 0.29 (0.18-0.43), ICU hospitalizations 0.15 (0.08-0.26) at the peak of the epidemic per 1,000 people. - When 40% or more of the contacts of the detected symptomatic infections are traced and they and their households quarantined, the ensuing reduction in transmission leads to a noticeable flattening of the epidemic curve and appears to effectively limit the possible resurgence of a second epidemic wave.

			The LET scenario allows relaxation of the social distancing interventions while maintaining the hospital and ICU demand at levels close to the health-care availability and surge capacity.
Limitations:	- Large uncertainties around SARS-CoV-2 and particularly the fractions of asymptomatic and sub-clinical cases and their transmission. - Age-specific severity are informed by individual-level data from China and other countries - Does not account for comorbidities/ pre-existing conditions - Does not account for seasonality - Does not include wide-spread use of masks and other personal protective equipment - Does not include possible reintroduction of SARS-CoV-2 from infected travelers		
Conclusions:	Testing, contact tracing strategies at scale, based on home isolation of symptomatic COVID-19 cases and the quarantine of a fraction of their contacts' household, has the potential to provide a viable course of action to manage and mitigate the epidemic when social distancing interventions are progressively lifted. Results indicate that gradually removing the restrictions imposed by social distancing could lead to a second wave with the potential to overwhelm the health care system if not combined with strategies aimed at the prompt testing of symptomatic infections and the tracing and quarantine of as many of their contacts as possible.		
Reference: Davies NG, Kucharski AJ, Eggo RM, Gimma A. The effect of non-pharmaceutical interventions on COVID-19 cases, deaths and demand for hospital services in the UK: a modelling study. CMMID COVID-19 working group, W. John Edmunds. https://www.medrxiv.org/content/10.1101/2020.04.01.20049908v1			*Jurisdiction*: UK - England, Wales, Scotland, and Northern Ireland
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/ Scenarios**	**Results**
To use a stochastic age-structured transmission model to explore a range of intervention scenarios, including the introduction of school closures, social distancing, shielding of elderly groups, self-isolation of symptomatic cases, and extreme "lockdown"-type restrictions. Authors simulated different durations of interventions and triggers for introduction, as well as combinations of interventions.	Assumptions: - Basic reproduction number, R_0 was 2.7 (95% credible interval: 1.6–3.9) across settings without substantial control measures in place (R_0 derived from meta-analysis). - Case Fatality Ratio that ranged substantially across age groups, from 0.1% in the 20–29 age group to 7.7% in the over-80 age group. - Lockdowns would be triggered at a national level rather than at a local level, and that the trigger threshold would not change over time. Parameters: - Latent period - Duration of preclinical infectiousness	Intensive Interventions Including a significant program of social distancing, with a particular impact on leisure activities; workers being asked to work from home where possible; shielding of both elderly (70+) individuals and people in high-risk-groups of all ages; school closures; and self-isolation of symptomatic individuals.	Results for the impact of longer-term and repeated interventions presented here. See paper for shorter 12-week intervention impacts. - Median and 95% prediction interval reported. Totals are calculated up to December 31, 2021. - Total Cases: 11M (6.6M-21M) - Total Deaths: 130K (73M-270M) - Proportion of time spent in lockdown (29-Jan 2020 to 31-Dec 2021: N/A Total Infected: 28M (18M-48M)
		Intensive Interventions + Lockdown with 1000 bed trigger (national-level) Lockdowns are periods of particularly strict restrictions on	- Total Cases: 4M (1.8M-12M) - Total Deaths: 51K (21K -170K) - Proportion of time spent in lockdown (29-Jan 2020 to 31-Dec 2021: 0.73(0.27-0.9) Total Infected: 11M (4.3M-33M)

Each scenario, includes projections on estimated new cases over time, patients requiring inpatient and critical care (intensive care unit, ICU) treatment, and deaths. Timeline: Simulations ran to December 31, 2021	- Duration of clinical infectiousness - Duration of subclinical infectiousness - Incubation period - Serial interval - Susceptibility to infection on contact - Probability of clinical symptoms on infection for age group I - Relative infectiousness of subclinical cases - Number of age/individuals contacted by an age/individual per day - Number of age/individuals - Time step for discrete-time simulation - Delay from onset to hospitalization (days) - Duration of hospitalization in non-ICU bed (days) - Duration of hospitalization in ICU beds (days) - Proportion of hospitalized cases that require critical care, delay from onset to death (days) 'Intensive Intervention' Scenarios - Assumed 30% of workers would be able to work from home, reducing work and transport (i.e., public transport [bus, train]) contacts (11% of 'other' contacts) among low-risk general population (assumed to be 90% of adults under age of 70) by 30% - Assumed leisure contacts (45% of 'other' contacts) would decrease by 75% in low-risk general population *leisure contacts defined as those mainly occurring in pubs, restaurants, bars and cinemas - Work and 'other' contacts reduced by 75% among high-risk general	movement Lockdowns phased in when ICU bed capacity reached certain thresholds, which would be kept in place until ICU bed usage fell back below the same trigger threshold, to then be brought in again as needed.	
		Intensive Interventions + Lockdown with 2000 bed trigger (national-level)	- Total Cases: 6.5M (3M-14M) - Total Deaths: 84K (34K-200K) - Proportion of time spent in lockdown (29-Jan 2020 to 31-Dec 2021: 0.61 (0.23-0.77) Total Infected: 18M (6.9M -36M)
		Intensive Interventions + Lockdown with 5000 bed trigger (national-level)	- Total Cases: 9.7M (5.2M-17M) - Total Deaths: 130K (60K-240K) - Proportion of time spent in lockdown (29-Jan 2020 to 31-Dec 2021: 0.35 (0.12-0.5) Total Infected: 27M (12M-41M)

	population (10% of under-70s) through shielding; *shielding for most-vulnerable in population: isolation from unnecessary contacts; not leaving the home except for front/back yard; not attending gatherings; not going shopping/running errands - Among aged 70+, assumed 75% of work and other contacts reduced through shielding; further reduced transport contacts by 30% and leisure contacts by 75%		
Limitations:	- The model does not explicitly structure individuals by household, therefore unable to evaluate the impact of measures based on household contacts, e.g. household quarantine, i.e., where all members of a household with a suspected COVID-19 case remain in isolation - Does not include individual level variation in transmission (i.e. 'super spreading events')		
Conclusions:	- The characteristics of SARS-CoV-2 mean that extreme measures are likely required to bring epidemic under control and to prevent very large numbers of deaths and excess of demand on hospital beds, especially those in ICUs. A scenario in which more intense lockdown measures were implemented for shorter periods may be able to keep projected case numbers at a level that would not overwhelm the health system.		
Reference: Kissler, Stephen M., Christine Tedijanto, Edward Goldstein, Yonatan H. Grad, and Marc Lipsitch. Projecting the transmission dynamics of SARS-CoV-2 through the post-pandemic period (2020). http://nrs.harvard.edu/urn-3:HUL.InstRepos:42639308			*Jurisdiction*: USA
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/ Scenarios**	**Results**
Used data from the United States to model beta coronavirus transmission in temperate regions and to project the possible dynamics of SARS-CoV-2 infection through the year 2025 Implemented a two-strain ordinary differential equation (ODE) susceptible-exposed-infectious-recovered	Assumptions: - latent period of 4.6 days - infectious period of 5 days - We allowed the cross-immunities, duration of immunity, maximum R_0, and degree of seasonal variation in R_0 to vary. - Assumed an establishment time of sustained transmission on 11 March 2020, when the World Health Organization declared the SARS-CoV-2 outbreak a pandemic - Entire population was assumed to be susceptible at the start of the simulation period	Summarized post-pandemic SARS-CoV-2 dynamics into the categories of annual outbreaks, biennial outbreaks, sporadic outbreaks, or virtual elimination. Assessed intermittent social distancing measures, for which social distancing was turned "on" when the prevalence of infection rose above a threshold and "off" when it fell below a second, lower threshold, with the goal of keeping the number of critical	Model simulations demonstrated the following key points. - In all modeled scenarios, SARS-CoV-2 was capable of producing a substantial outbreak regardless of establishment time. Spring/summer establishments favored outbreaks with lower peaks, whereas autumn/winter establishments led to more acute outbreaks - Short-term immunity (~40 weeks, similar to HCoV-OC43 and HCoV-HKU1) favors the establishment of annual SARS-CoV-2 outbreaks, whereas longer-term immunity (2 years) favors biennial outbreaks

(SEIR) compartmental model to describe the transmission dynamics of HCoV-OC43 ('strain 1') and HCoV-HKU1 ('strain 2') in the United States. Not stratified by age. Timing: The model was run for 24.5 years to allow the dynamics to reach a steady state, and then the simulated incidence of Strain 1 and Strain 2 were compared with the percent test-positives multiplied by percent of clinic visits for ILI for HCoV-OC43 and HCoV-HKU1, respectively	Parameters: - incidence proxy calculated by multiplying the weekly percentage of positive tests for each coronavirus by the weekly population-weighted proportion of physician visits due to influenza-like illness (ILI) The assumptions needed for this proxy to capture true influenza incidence up to a multiplicative constant are described in Goldstein et al. (2011) - Daily effective reproduction number (Ru) based on case counts and the generation interval distribution - basic reproduction number, R_0, was assumed to be seasonal with a period of 52 weeks, specified by the equation - Infection was introduced through a brief, small pulse in the force of infection (an increase of 0.01/week for one half week) for each strain within the first year of the simulation, simulating the establishment of sustained person-to-person transmission. - Used a hill-climbing algorithm to identify the maximum likelihood parameter values, using the best-fit parameter combination from the LHS scheme as initial conditions - R_0 No details on NPI/social distancing assumptions/parameters	care patients below 0.89 per 10,000 adults. - An "on" threshold of 35 cases per 10,000 people achieved this goal in both the seasonal and non-seasonal cases with wintertime R_0 = 2.2. - Chose five cases per 10,000 adults as the "off" threshold - Evaluated the impact of one-time social distancing efforts of varying effectiveness and duration on the peak and timing of the pandemic with and without seasonal forcing.	- A 40% summertime decline in R_0 would reduce the unmitigated peak incidence of the initial SARS-CoV-2 pandemic wave. However, stronger seasonal forcing leads to a greater accumulation of susceptible individuals during periods of low transmission in the summer, leading to recurrent outbreaks with higher peaks in the post-pandemic period. - Low levels of cross-immunity from the other betacoronaviruses against SARS-CoV-2 could make SARS-CoV-2 appear to die out, only to resurge after a few years: even if SARS-CoV-2 immunity only lasts for 2 years, mild (30%) cross-immunity from HCoVOC43 and HCoV-HKU1 could effectively eliminate the transmission of SARS-CoV-2 for up to 3 years before a resurgence in 2024, as long as SARS-CoV-2 does not fully die out - Although the frequency and duration of the social distancing measures were similar between the scenarios, the pandemic would conclude by July 2022 and social distancing measures could be fully relaxed by early to mid-2021, depending again on the degree of seasonal forcing of transmission. - None of the one-time interventions were effective at maintaining the prevalence of critical cases below the critical care capacity - Increasing critical care capacity allows population immunity to be accumulated more rapidly, reducing the overall duration of the pandemic and the total length of social distancing measures - Under all scenarios, there was a resurgence of infection when the simulated social distancing measures were lifted. However, longer and more stringent temporary social

			distancing did not always correlate with greater reductions in pandemic peak size - Overall, shorter durations of immunity and smaller degrees of cross immunity from the other betacoronaviruses were associated with greater total incidence of infection by SARS-CoV-2, and autumn establishments and smaller seasonal fluctuations in transmissibility were associated with larger pandemic peak sizes.
Limitations:	- Only five seasons of observational data on coronaviruses were available, though the incidence patterns resemble those from 10 years of data from a hospital in Sweden - Spline coefficients were constant across all seasons though seasonal forcing likely differed from year to year based on underlying drivers - No difference in the seasonal forcing, per-case force of infection, incubation period, or infectious period across beta coronaviruses - Did not directly model any effect from the opening of schools, which could lead to an additional boost in transmission strength in the early autumn, or any effects of behavior change or control efforts, which could suppress the effective reproduction number - Transmission model is deterministic, so it cannot capture the possibility of SARS-CoV- 2 extinction - Did not have sufficient data to parameterize an age-structured model - Accurately quantifying the probability of SARS-CoV-2 extinction would depend on many factors for which sufficient evidence is currently lacking.		
Conclusions:	- Total incidence of COVID-19 illness over the next five years will depend critically upon whether or not it enters into regular circulation after the initial pandemic wave, which in turn depends primarily upon the duration of immunity that SARS-CoV-2 infection imparts. - Intensity and timing of pandemic and post-pandemic outbreaks will depend on the time of year when widespread SARS-CoV-2 infection becomes established and, to a lesser degree, upon the magnitude of seasonal variation in transmissibility and the level of cross immunity that exists between the beta coronaviruses. - Prolonged or intermittent social distancing may be necessary into 2022. - Authors do not take a position on the advisability of the findings.		
Reference: Barbarossa MV, Fuhrmann J, Heidecke J, Vinod Varma H, Castelletti N, Meinke JH, et al. A first study on the impact of current and future control measures on the spread of COVID-19 in Germany. medRxiv [Internet]. 2020 Available from:http://medrxiv.org/content/early/2020/04/11/2020.04.08.20056630			*Jurisdiction:* Germany
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/ Scenarios**	**Results**
Present preliminary results of a mathematical study directed at predicting the spread of virus and to evaluate the impact of	Assumptions: - Only 25% of infectives remain undetected, meaning that the number of infectives at a given time is 1.35	Do-nothing scenario	Peak in the curve of diagnosed cases at the end of April 2020, with about 2.8 million active detected cases on the day of the peak, a total of 80 million infected (out of which only about 8 million detected and 23.5 million asymptomatic

non-pharmaceutical interventions in Germany – The proposed approach extends the known S-E-I-R (susceptible-exposed-infected-recovered) scenario for disease dynamics - Six different age groups are reported: 0-4years, 5-14years, 15-34years, 35-59years, 60-79 years and 80+ years. Timeline: Model predictions until January 2021	times the number of known active cases - Population is homogeneous (in particular with respect to age and social habits) - Reducing contacts: child-child (-60%), child-adult (-5%), adult-adult (-50%), senior-senior (- 10%). Assumed to be applied at national scale on March 14th 2020 - Reducing contacts: child-child (-20%), child-adult (- 20%), adult-adult (-50%), child-senior (-30%), adult-senior (--30%), senior-senior (- 30%). Assumed to be applied at national scale from March 13th (day 45), contact reductions fully achieved after 13 days - Information and media activities increase social distancing and personal hygiene (e.g., washing hands), limited (self) quarantine of known or suspected cases starting on Feb 25th - Increased testing activity since Feb28th - Identified infected cases isolated for 2 weeks Parameters: - Reproduction number (R_0) - Age group - Diagnosed cases - Testing capacity - Immunological stages during infections - General increased awareness in population due to effect of media - Active control due to main intervention measures		SARS-CoV-2 infections), and a total of 630,000 fatalities over the course of the epidemic
		Adopted main control measures Closure of schools and universities, remote working policy, isolation of infected cases and maintenance of testing activity as of March 2020	- Shift in the epidemic peak by about one month (expected in early June 2020) - A reduction of detected SARS-CoV-2 infections by 60% (from 2.8 million to 1.26 million) at the outbreak peak - A reduction by about 100,000 fatalities (expected over 530,000 fatalities in total) About 69 million infected (thereof 20 million asymptomatic SARS-CoV-2 infections) over the course of the epidemic
		Enriched baseline measures (with increased testing capacity)	- Reduce number of fatalities to minimum of 18,000 and peak number of infectives to 600,000 active detected infections at day of peak in third week of April Preventing new infections also slows down increase of number of recovered, and immune
		Partial lifting of restrictions	- Increase of some 15% of the death toll over the BSL scenario by the model - Epidemic peak around mid-May 2020, 2.2 million diagnosed cases on the day of the peak and 620,000 fatalities over the course of the epidemic If accompanied by increased testing, the (first) epidemic peak would be reached due to increased testing activity in the second half of April 2020, with 670,000 detected SARS-CoV-2 infections at the outbreak peak. A second peak would follow and the epidemic would last for a longer period (more than one year), but the total number of cases (14.4 million, out of which there are 1.2 million asymptomatic SARS-CoV-2 infections) and fatalities (about 60,000) would be substantially limited by the measures
		Close to total shutdown of economic/social activities for period of 5 weeks	- scenario would still lead to about 570.000 fatalities in total - If accompanied by increased test activity this scenario leads to similar fatality numbers (258,000) and even higher peak numbers of

	Social distancing control measures: - Closures of all schools, universities, sports clubs and cancelling public events - Reduced contact in essential workplaces and outside the household (i.e. public transport) - Remote working policy (home office) - Closure of all restaurants and bars		known infected individuals (22.6 million) as compared to a scenario with increased testing alone as additional measure Main effect of a shutdown with abrupt start and end would be delaying the peak of known active cases, while at the same time making it narrower and higher
Limitations	- There is significant uncertainty regarding the current number of undetected cases and therefore the current detection ratio - Limited capacity of the health care system, in particular of intensive care units, was not yet directly considered as a parameter of refined model - Aggressiveness of the virus and hence the mortality among all affected individuals (whether diagnosed or not) is another unknown, but different assumptions about this parameter can be expected to have similar impacts on all the scenarios - Difficult to judge effects of interventions already in place on contact rates with sufficient precision		
Conclusions	- A combination of vastly increased testing, isolation of known infectives, and restraint in contacts with persons of high age or with relevant preconditions is the most promising approach if the severity of the epidemic is to be limited to as low a level as possible.		
Reference: Chowdhury R, Heng K, Shawon MS, Goh G, Okonofua D, Ochoa-Rosales C, Gonzalez-Jaramillo V, Bhuiya A, Reidpath D, Prathapan S, Shahzad S. Dynamic interventions to control COVID-19 pandemic: a multivariate prediction modelling study comparing 16 worldwide countries. *European Journal of Epidemiology*. 2020:1-1. https://doi.org/10.1007/s10654-020-00649-w			*Jurisdiction* Europe, data from Australia, Belgium, Chile, Netherlands, Columbia, Mexico, South Africa, Sri Lanka, Bangladesh, India, Nigeria, Pakistan, Afghanistan, Burkina Faso, Tanzania, Uganda
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/ Scenarios**	**Results**
Employed a multivariate prediction model, based on up-to-date transmission and clinical parameters, to simulate outbreak trajectories in 16 countries, from diverse regions and	Assumptions: - Basic reproduction number (R0) of 2.2 - Effective reproduction numbers, R, average number of secondary cases per infectious case in presence of control measures and a partially immune population) of 0.8 and 0.5 for	No intervention	- Number of cases requiring ICU care would exceed the available capacity significantly for every single country - In aggregate, would also result in 7,840,444 deaths in all 16 countries, majority of these deaths will occur in India, proportionate to the large population of country - Duration of epidemic will last nearly 200 days in the majority of included countries

economic categories. Includes age-standardized estimates. Assumed parameters for transmission dynamics yielded a characteristic rise-and fall timescale of infections of about 50 days, which was set to be the illustrative duration of intervention; Choosing a slightly longer period (e.g. 60 days) yielded similar outcomes	mitigation and suppression interventions, respectively Parameters: - Case isolation at home - Voluntary home quarantine - Closure of schools/universities - Social distancing of entire population Social distancing intervention measures include (supplementary to above parameters): - Shielding of vulnerable groups - Restricting large public events/gatherings	Consecutive cycles of mitigation (e.g., combination of measures, such as general social distancing measures, hygiene rules, case-based isolation, shielding of vulnerable groups, school closures or restricting of large public events; target R = 0.8)	- Simultaneous cycles of 50-day mitigation intervention followed by a 30-day relaxation would likely to reduce the effective reproduction number R to 0.8 in all countries - Rolling mitigation measure insufficient to keep number of patients requiring healthcare below available critical care capacity - Mitigation interventions effective at first 3 months for all countries, but after first relaxation, pandemic would exceed hospital capacity in all countries and result in 3,534,793 deaths
		Consecutive cycles of suppression (e.g., additional measures of strict physical distancing, including lockdowns; target R = 0.5, followed by a relaxation period)	- Dynamic cycles of 50-day suppression followed by a 30-day relaxation, aimed at reducing the effective R to 0.5, were suitable for all settings to keep ICU demand within national capacity - Such approach would result in longer pandemic, beyond 18 months in all countries; however, global mortality would drop to 131,643 during period
		Continuous suppression measure with no relaxation	- Single but continuous yearlong mitigation or suppression strategy would be effective to keep number of patients well below available hospital capacity - In case of suppression, in 3 months, most of countries would not have any new cases to report - In case of sustained mitigation, countries would require approximately 6.5 months to reach a no-new-case scenario
Limitations	- In the absence of country-specific, real-time, reproduction numbers for the epidemic, assumed a constant transmission rate during each modeled cycle. - The age-standardization analyses were based on public sector surveillance data, which may not be robust for all LMIC and LIC countries, with potentials for underestimation of cases and deaths. - Furthermore, given unavailability of relevant data, we were Inability to adjust for wider social and economic costs of the dynamic approaches owing to unavailability of relevant - As with all COVID-19 models, analyses were based on several transmission parameter assumptions		
Conclusions	- Intermittent reductions of *R* below 1 through a potential combination of suppression interventions and relaxation can be a pragmatic strategy for COVID-19 pandemic control. Such a “schedule” of social distancing might be particularly relevant to		

	low-income countries, where a single, prolonged suppression intervention is unsustainable. Efficient implementation of dynamic suppression interventions worldwide, therefore, would help: (1) prevent critical care overload and deaths, (2) gain time to develop preventive and clinical measures, and (3) reduce economic hardship globally		
Reference: Prem K, Liu Y, Russell TW, Kucharski AJ, Eggo RM, Davies N, Flasche S, Clifford S, Pearson CA, Munday JD, Abbott S. The effect of control strategies to reduce social mixing on outcomes of the COVID-19 epidemic in Wuhan, China: a modelling study. The Lancet Public Health.2020;5(5), e261-e270. https://doi.org/10.1016/S2468-2667(20)30073-6			*Jurisdiction*: Wuhan, China
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/ Scenarios**	**Results**
Simulated the ongoing trajectory of an outbreak in Wuhan using an age-structured susceptible-exposed-infected-removed (SEIR) model for several physical distancing measures; Fitted the latest estimates of epidemic parameters from a transmission model to data on local and internationally exported cases from Wuhan in an age-structured epidemic framework and investigated the age distribution of cases Simulated lifting of the control measures by allowing people to return to work in a phased-in way and looked at the effects of returning to work at different stages of the underlying outbreak (at beginning of March or April)	Assumptions: - Wuhan to be a closed system with a constant population size of 11 million - Younger individuals are more likely to be asymptomatic (or subclinical) and less infectious than older individuals - No heterogeneity in susceptibility between children - Children and adults were equally transmissible, other than the differences in their contact rates Parameters: - Basic reproduction number - Average incubation period - Average duration of infection - Initial number of infected - Pr (infected case is clinical) (0 or 0-4) - Pr (infected case is clinical) (0 or 0-8) - Pr (infection acquired from subclinical) Social mixing interventions: - Varied location types - No school term break – during Winter - No contact via persons celebrating Lunar New Year holidays - School break – during Winter (school-going individuals did not have any contacts at school because of school holidays from Jan 15, to Feb 10, 2020)	First scenario - Theoretical, assumed no change to social mixing patterns at all location types, no school term break, and no Lunar New Year holidays	- Resulted in the highest number of cases per day at peak during late March 2020 (~75,000 new cases per day)
		Second scenario - No interventions, winter school break in Wuhan, and Lunar New Year holidays - No physical distancing control measures, school-going individuals did not have any contacts at school because of school holidays	- Among individuals aged 55 to <60 years and 10 to <15 years, the standard school winter break and holidays for the Lunar New Year would have had little effect on progression of the outbreak had schools and workplaces reopened as normal
		Third scenario - Intense control measures in Wuhan to contain outbreak - Assumed school closure and 10% of workforce (e.g. healthcare, police, essential govt staff) working during control measures - Staggered return to work while school remained closed (i.e., 25% of the workforce working in weeks one and two, 50% of the workforce working in weeks three and four, and 100% of the workforce working and school resuming)	- Reduced cumulative infections by end-2020 and peak incidence, while also delaying the peak of the outbreak - Effects of physical distancing strategies vary across age categories; the reduction in incidence is highest among school children and older individuals and lowest among working-age adults - Modelled effects of the intense control measures of prolonged school closure and work holidays vary by the duration of infectiousness - Short duration of infectiousness (3 days), relaxing physical distancing measures could avert 30% of cases in school children/older individuals

Deterministic stage-structured SEIR model over a 1 year	- Workplace physical distancing; staggered return to work – see third scenario column to right - Reduction in social mixing in community (e.g., via shopping, commuting)		- Fewer cases could be averted by end-2020 should the disease have a longer duration of infectiousness (e.g., 7 days)
Limitations	- Compartmental model does not capture individual-level heterogeneity in contacts - Compartmental model is not equipped to explicitly consider transmission within health-care institutions and households - Used an existing model that inferred time-dependent R_e based on the growth of reported cases in Wuhan and the number of exported cases outside China originating from Wuhan – underlying Re in Wuhan could have been larger - Have not incorporated climatic factors - Assumed children and adults are equally transmissible		
Conclusions	- Non-pharmaceutical interventions based on sustained physical distancing have strong potential to reduce magnitude of the epidemic peak of COVID-19 and lead to a smaller number of overall cases. Lowering and flattening of the epidemic peak is particularly important, as this reduces the acute pressure on the health-care system. Premature and sudden lifting of interventions could lead to an earlier secondary peak, which could be flattened by relaxing the interventions gradually.		
Reference: Zhang Y, Hota M, Kapoor S. Strategic release of lockdowns in a COVID infection model. medRxiv [Internet]. 2020 Available from: http://medrxiv.org/content/early/2020/05/15/2020.05.10.20096446.abstract			*Jurisdiction*: States of Illinois and New York, USA
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/ Scenarios**	**Results**
Using the SIR model for epidemic spread, design and implement a method to determine the earliest time of release from lockdown restrictions, constrained by a specified threshold on the subsequent peaks of infection. The focus of paper is to illustrate the relationship between the growth of infection and release of population from lockdown. Not stratified by age. Timeline: models projects out between 440-1400 days	Assumptions: - The population size, N remains constant - At the onset of the spread of infection, h is a function of time, i.e., h(t), to be a constant - All places release the lock down at the same time - Lockdown begins when 200 people are infected - 50% of the population in Illinois and New York is under "lockdown" after the number of infections hit a figure of 200 Parameters: - Size of susceptible population - Number of infected individuals - Number of recovered individuals	Phased removal of restrictions - A fraction of the population, that is under lockdown is eliminated from the population in the system, and this fraction is re-introduced at later stages - Two scenarios (a) 2 weeks after the number of new cases peak and (b) 2 weeks after the peak of the active infected cases	- Releasing population in phases will result in increase in number of infections - If the health-care system has the capacity to handle 75% of the first peak, then the release of the lockdown should be at around 50% drop from the peak active cases
		Graded removal of restrictions - A percentage, of the original population under lockdown is released linearly, starting at 14 days after the peak	- An adaptive gradual release policy with variable rate, results in maintaining reduction in active infected cases and provides a relatively fast release of the population from lockdown

<table>
<tr><td></td><td>No details on NPI/social distancing assumptions/parameters</td><td></td><td></td></tr>
<tr><td>Limitations:</td><td colspan="3">- Assumes several parameters as constant for the sake of simplicity
- Large uncertainty owing to limitations of SARS-CoV-2 parameters and assumptions</td></tr>
<tr><td>Conclusions:</td><td colspan="3">A gradual reopening at a rate of 1.5% of the population under lockdown results in a spike of cases; Impact of infection transmission rates – relationship with threshold rate; can be used to determine lockdown release expressed as % of peak of active infections, given threshold % of the first peak of active infection cases that can be afforded by the health care system with stress.; E.G: if the health-care system has the capacity to handle 75% of the first peak, then the release of the lockdown should be at around 50 percent drop from the peak active cases in Illinois. For New York, the corresponding drop is estimated at 50%.</td></tr>
<tr><td colspan="3">Reference: Gel E, Jehn M, Lant T, Muldoon A, Nelson T, Ross HM. COVID-19 Healthcare Demand Projections: Arizona. medRxiv. 2020 Jan 1. https://www.medrxiv.org/content/10.1101/2020.05.13.20099838v1</td><td>Jurisdiction: Arizona, USA</td></tr>
<tr><td>Purpose and Timeline</td><td>Assumptions and Parameters</td><td>Interventions/ Scenarios</td><td>Results</td></tr>
<tr><td rowspan="3">A mathematical framework that ties disease surveillance with future burden on Arizona's hospital system and hospital resources; compartmental system dynamics model using an SEIRD framework that includes multiple compartments for infected individuals; allows estimate of the number of patients in hospital and assess model with respect to two sources of data: daily new cases/ cumulative reported deaths over time. Not stratified by age.

Used bin initialization logic coupled with a fitting technique to construct projections</td><td rowspan="3">Assumptions:
- Constant transmission rates
- Detection of ¼ actual cases
- Relatively high asymptomatic rate (40%)
- Deaths are primarily occurring in the ICU
- Information on reported deaths is relatively accurate
- Presymptomatic duration is 2 days

Parameters:
- Time to infectiousness
- Presymptomatic duration
- Asymptomatic infectious period
- Mild infection recovery time
- Severe infection recovery time
- Critical infection to death
- Additional days to recover in ICU
- Fraction of asymptomatic cases
- Fraction of mild asymptomatic cases
- Fraction hospitalized on regular bed
- Fraction hospitalized progressing to ICU
- Mortality among ICU patients</td><td>1X loading scenario

* X-factor initialization scheme where the X-factor is multiplied the number of eventually detected-exposed individuals to obtain the underlying overall exposures on a given presumed exposure day</td><td>- Approx. 4000 new exposures, 1500 deaths, 25,000 total infections and 2100 hospitalized patients by June 23, 2020</td></tr>
<tr><td>4X loading scenario</td><td>- Approx. 12,000+ new exposures, 3000+ deaths, 85,000 total infections and 8100 hospitalized patients by June 23, 2020
- Presumed exposures and deaths for 4X loading under different increase scenarios: gradual increases of 10% on 5/15, 20% on 6/1, 30% on 6/15 and slow increases 5% on 5/15, 15% on 6/1 and 30% on 6/15 (each from baseline) – 25,000+ new exposures by June 23 and 10,000 deaths by July 7, 2020</td></tr>
<tr><td>6X loading scenario</td><td>- Approx. 12,000+ new exposures, 3000+ deaths, 120,000+ total infections and 12,000+ hospitalized patients by June 23, 2020</td></tr>
</table>

Simulation from day 0 (March 31) to September 15, 2020; 6-month	Transmission rate, βt, a good way of thinking about impact of NPI interventions (i.e., social distancing [keeping 6+ feet apart], stay-at-home-orders, school closures, etc.) and how interventions impact average number of infectious individuals that susceptible individuals contact, or probability of transmission given contact		
Limitations:	- This model iteration was constructed based on the stated Arizona stay-at-home model remaining in place until 5/15 - Large uncertainty as with all models for SARS-CoV-2 parameters and assumptions		
Conclusions:	- After model was constructed based on the 5/15 reopening expectation, the Arizona governor announced on 5/4 that businesses, including salons and dine-in restaurants, would begin reopening between 5/8 and 5/11. Anticipate that projections will shift in future iterations based on these policy changes		
Reference: Perkins A, Espana G. Optimal control of the COVID-19 pandemic with non-pharmaceutical interventions. medRxiv. 2020 Jan 1. https://www.medrxiv.org/content/10.1101/2020.04.22.20076018v1			*Jurisdiction*: United States
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/ Scenarios**	**Results**
To characterize a range of possible strategies for control and to understand their consequences, performed an optimal control analysis of a mathematical model of SARS-CoV-2 transmission to model out transmission, hospitalization and deaths. Not age stratified. Apply optimal control theory to determine optimal strategies for the optimal strategies for the implementation of NPIs to control COVID-19 Calibrated model to data from the US and focused analysis on optimal controls from May 2020 through December 2021.	Assumptions: - Density dependent transmission only requires specification of susceptible/infectious classes in transmission term - Rates of birth and death due to reasons other than COVID-19 are equal - Vaccination may not provide complete protection Parameters: - Transmission coefficient - Background birth/death rates - Probability of death among hospitalized cases - Progression through hospitalization - Timing of vaccine introduction - Vaccination rate - Hospital capacity - Maximum effect of control NPIs include:	Optimal control - NPI-based optimal control required is dependent on model parameters - Optimal level of NPI control moving forward *Model was calibrated to 18 scenarios. Scenarios are categorized within larger buckets of 'optimal' and 'optimal following different starting conditions' Optimal control includes the following NPIs: Social distancing, testing, contact tracing and case isolation.	- Under c = 10^-12, u*(t) remains at u-max until late June 2020, Hospitalizations drop from their peak in April 2020 and remain very low through 2021; the susceptible population remains very high and only begins eroding once a vaccine is introduced - Higher value of c = 10^-9, u*(t) drops to around 50% of u-max in May 2020; hospitalizations rebound and exceed hospital capacity by around a third in June and July before falling again - Highest value of c = 10^-6, u*(t) drops almost to zero at the beginning of May 2020, rapid increase in hospitalizations - Large second wave in summer exceeds hospital capacity by 20-fold and results in cumulative deaths equaling 5% of population
		Optimal control following different starting conditions - Delays in initiating of control NPI measures	- Cumulative deaths through 2020 and 2021 decrease when control begins earlier and increase when control begins later - A delay in the initiation of control has the smallest effect - cumulative deaths increase by 10% with a three-week delay

	- School closures - Work from home policies - Shelter in place mandates - Case isolation based on self-awareness of symptoms - Social distancing (physical distance [6+feet apart])	The **parameter c** weights the extent to which the control, u(t), is prioritized for minimization relative to deaths, D(t) ***U* parameter** - Control with non-pharmaceutical interventions (optimal control) **D parameter** – deaths	- Delay in the initiation of control has the largest effect - cumulative deaths increase 28-fold with a three-week delay - Overall amount of time spent under control throughout 2020 and 2021 increases when control begins earlier and decreases when control begins later - Delays in initiation of control result in a higher prevalence of infection by the beginning of the optimization period, which results in higher levels of subsequent transmission, greater depletion of the susceptible population, and less need for control later in the period of optimization
Limitations:	- Omission of subnational variation in epidemic dynamics - differentiation among alternative NPIs - age differences in contact patterns and risk of hospitalization - deterministic nature and the rudimentary calibration procedure performed, which was sufficient to provide a basis for qualitative analyses but that would need refinement for application of model to inference or forecasting		
Conclusions:	Analysis suggests that decisions about the continuation or relaxation of NPI-based control strategies could have major implications for the possibility of keeping transmission below levels that health systems can cope with. At the same time, analysis highlights the role that constraints play in determining optimal levels of control going forward, both in terms of constraints on epidemiological parameters and on levels of control prior to the time that a decision is made about future actions. Going forward, reducing transmission in the near term would give decision makers greater flexibility in the range of decisions available to them in the future, and gathering high-quality data could help reduce uncertainty about the consequences of those decisions.		

Reference: Ferguson NM, Laydon D, Nedjati-Gilani G, et al. Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. Imperial College London.2020. https://www.imperial.ac.uk/media/imperial-college/medicine/mrc-gida/2020-03-16-COVID19-Report-9.pdf Accessed May 26, 2020.			*Jurisdiction*: UK (Great Britain specifically) and the US.
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/ Scenarios**	**Results**
To 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.	Assumptions: - incubation period of 5.1 days - 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, R0=2.4	Suppression strategies for GB. Impact of three different policy options on the total number of deaths seen in a 2-year period and peak demand for ICU beds. Social distancing and school/university closure are triggered at a national level when weekly numbers of new COVID-19 cases	

Age stratification was included in the model. Timeline: 2 years	but examine values between 2.0 and 2.6, - symptomatic individuals are 50% more infectious than asymptomatic individuals - individuals are assumed to be immune to re-infection - 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. - two-thirds of cases are sufficiently symptomatic to self-isolate (if required by policy) within 1 day of symptom onset, - mean delay from onset of symptoms to hospitalization of 5 days - IFR of 0.9% with 4.4% of infections hospitalized - 30% of those that are hospitalized will require critical care (invasive mechanical ventilation or ECMO) - 50% of those in critical care will die and an age-dependent proportion of those that do not require critical care die - 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, 30% of hospitalized cases requiring critical care Parameters:	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.	
		3 interventions (case isolation + home quarantine + social distancing)	Total Deaths: - On Trigger 60 - Do nothing: 410,000 - CI_HQ_SD 47,000 Peak ICU Beds - Do nothing: 130,000 - CI_HQ_SD: 3,300 Proportion of time with SD in place: 96%
		3 interventions (school/university closure + case isolation + social distancing)	Total Deaths: - On Trigger 60 - Do nothing: 410,000 - PC_CI_SD 6,400 Peak ICU Beds - Do nothing: 130,000 - PC_CI_SD: 930 Proportion of time with SD in place: 69%
		4 interventions (home quarantine + school/university closure + case isolation + social distancing)	Total Deaths: - On Trigger 60 - Do nothing: 410,00 - PC_CI_HQ_SD: 5,600 Peak ICU Beds - Do nothing: 130,000 - PC_CI__HQ_SD: 920 Proportion of time with SD in place: 58% **See paper for more Triggers and R0 scenarios**

	- Contacts with other individuals in the population, within the household, at school, in the workplace and in the wider community NPI parameters for intervention: - Case isolation in home: symptomatic cases stay home for 7 days, reducing non-household contacts by 75%; household contacts remain unchanged; assumed 70% household compliance - Voluntary home quarantine: following identification of symptomatic case, all household members remain home at least 14 days; household contact rates double during period, contacts in community reduce by 75%; assumed 50% household compliance - Social distancing of age 70+: reduce contacts by 50% in workplaces; increase household contacts by 25%; school contact rates remain unchanged; workplace contacts reduced by 25%; household contacts assumed to rise by 25% - Social distancing of entire population: all households reduce contact outside household, school or workplace by 75%' school contact rates unchanged, workplace contact rates reduced by 25%; household contact rates assumed to increase by 25% - Close schools/universities: closure of all schools, 25% of universities remain open; household contact rates for student families increase by 50% during closure; contacts in community increase by 25% during closure		
Limitations:	- Limitations in surveillance data for both countries		

	- Uncertainty owing to assumptions required for SARS-CoV-2 parameters - This report lacks detail on model construction, calibration, etc.
Conclusions:	- 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. Overall, results suggest that population-wide social distancing applied to the population as a whole would have 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 immunize the population. 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.

Reference: Neto OP, Reis JC, Brizzi ACB, Zambrano GJ, de Souza JM, Amorim WPE, et al. COVID-19 mathematical model reopening scenarios for Sao Paulo - Brazil. medRxiv [Internet]. 2020 Available from: http://medrxiv.org/content/early/2020/05/01/2020.04.26.20081208.abstract			*Jurisdiction:* Sao Paulo, Brazil
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/ Scenarios**	**Results**
To produce a generalized computational model to predict consequences of various reopening scenarios on COVID-19 infections rates and available hospital resources in São Paulo – Brazil. Model is age-structured. Timelines: Model forecasts from February – December 2020	Assumptions: - Whole population is susceptible to the disease - Number of deaths is more reliable to measure of epidemic - Mortality rate constant across countries, considering only age differences in populations - Cell-phone data is an accurate measure of social distancing Parameters: - Fraction of infectious that are asymptomatic - Fraction of hospitalized that become critical case - Fraction of people in critical care who died - Infected values - Exposed values - Hospitalized values - Critical cases values - Dead values - Recovered values	Model ran 50 different scenarios, considering Brazil's data on April 25th, reopening on May 11, and SD ranging from 0-0.53 (current estimate for Brazil during quarantine)	- R_0 found was 3.88 for Brazil and 3.53 for São Paulo State - Latent periods of 0.3 and 0.5 days and infectious period of approximately 8 days for Brazil and São Paulo, respectively - Hospitalization periods of 4.4 days and ICU period of 13.4 days for both Brazil and São Paulo - Changes to either SD or protection rate can cause quite different outcomes - Minimum social distance that should be adopted by both the country of Brazil and the state of São Paulo would be 40%; the current values for the country and State now during quarantine are 53 and 54% - Varying SD from 13 to 40% cause a drop in model results of 18,754,357 to 3,412,191 in total infections, 184,781 to 34,000 in deaths, 1,905,610 to 199,940 in total hospitalizations, 39,291 to 10,566 in peak hospitalization in one day, 353,659 to 65,072 total ICU beds used, 37,023 to 9,086 peak ICU beds used in one day and 18,569,577 to 3,378,191 in recovered people

	Social distancing parameter: - Variable estimates percentual change in time of staying home during quarantine compared to before - No extensive details; however, mention of social distancing as 'physical distancing, closure of non-essential businesses'		- Adopting an approximate 20% over a 40% SD strategy after coming back from quarantine can result in an approximate double of the number of deaths (approximate form 28 thousand to 57 thousand) - When testing limited to severely ill individuals, mortality rates likely inflated - Demographics of population may account for differences in mortality rates between countries
Limitations	- Model assumes mortality rate was constant for all countries, considering only differences in age across the populations - applied a correction in the confirmed cases to our model, correcting by the age of the population. - Cell-phone data is an accurate measure of social distancing; and, for Brazil, that differences in google and cell-phone estimates from the state of São Paulo can be reflected across the country.		
Conclusions	- To prevent the spread of COVID-19 most countries have adopted social distancing policies and closed all non-essential businesses. Such measures have caused great economic suffering with government leaders under increasing pressure to reopen economies despite the continued threat of COVID-19 on public health. Model was able to provide a predicted scenario in which re-opening could occur with minimal impact on human life considering people careful behavior in combination with continued social distancing measures.		
Reference Keeling MJ, Hill E, Gorsich E, Penman B, Guyver-Fletcher G, Holmes A, et al. Predictions of COVID-19 dynamics in the UK: short-term forecasting and analysis of potential exit strategies. medRxiv [Internet]. 2020 Available from:http://medrxiv.org/content/early/2020/05/11/2020.05.10.20083683.abstract			*Jurisdiction:* United Kingdom
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/ Scenarios**	**Results**
To present a deterministic, age-structured transmission model that uses real-time data on confirmed cases requiring hospital care and mortality to provide up-to-date predictions on epidemic spread in ten regions of the UK	Assumptions: - Susceptibility and disease detection were dependent upon age, although the partitioning between these two components is largely indeterminable - All within household transmission is generated by the first infection within the household Parameters:	Current lockdown measures	- Number of daily deaths 206 would peak in April across all regions before starting to decline - England and Wales are found to be most severely affected, with the highest number of predicted deaths per capita, whilst a lower number of deaths per capita in Scotland and Northern Ireland - Under continued total lockdown, the average total deaths would be approximately 39,000

Timeline: Simulated a suite of scenarios to assess the impact of differing approaches to relaxing social distancing measures from 7th May 2020 to July 2021	- Age-dependent transmission, split into household, school, work and other - Rate of progression to infectious disease - Recovery rate, changes with τ, the relative level of transmission from undetected asymptomatics compared to detected symptomatics - Scales whether age-structure case reports are based on age-dependent symptoms (α = 0) or age-dependent susceptibility (α = 1) - Relative level of transmission from asymptomatic compared to symptomatic infection - Age-dependent probability of displaying symptoms (and hence being detected), changes with α and τ - Age-dependent susceptibility, changes with α and τ - Compliance - Household quarantine proportion - Population size of a given age Modelling social distancing - Contact matrices used to predict household transmission to transmission from age group-age group, school-based, work-based and transmission in all other locations - Assumed social distancing acted to reduce work, school and other matrices while increasing household contacts	Age-independent relaxation of lockdown measures	- Epidemic rapidly resurges with a peak in daily deaths of over 4,000 occurring in late June - Project intensive care unit occupancy to near 10,000 by the end of June - May be a slight resurgence in cases in the short term, hospital and ICU occupancy remained within capacity - For simulations in which more severe lockdown remains in place after 7th May, a second infection wave is predicted in 2021, when all social distancing measures are removed
		Age-dependent relaxation of lockdown measures	- For simulations in which more severe lockdown remains in place after 7th May, a second infection wave is predicted in 2021, when all social distancing measures are removed - Significant second wave in 2021 when isolation includes these younger age groups - When isolation is only in place for older age groups, a large initial wave of infection occurs during 2020, but a subsequent secondary wave is not observed - Continuing lockdown for the over 60s throughout 2020 whilst relaxing measures of the remainder of the population results in, on average, 138,000 deaths by the end of 2021 - Considering the overall impact from 2020-2021, a strategy of continuing lockdown measures for anyone over the age of 65 minimizes the total number of deaths, and continuing these measures for anyone over the age of 60 minimizes hospital and ICU occupancy, though the overall effect of this when compared with other age-related lockdown policies is marginal - As the age-threshold at which shielding is implemented increases, the total number of days for which ICU bed occupancy exceeds

			4,000 increases, implying that only shielding older age groups may put severe demands upon the health service
		Full relaxation of lockdown measures with region-based reintroduction when occupancy of intensive care units exceeded a given capacity (i.e., 45 ICU cases per million within the given region) and relaxed again when ICU occupancy declines	- Second, smaller peak in late May, with ICU and hospital occupancy remaining at manageable levels - The number of deaths and confirmed cases gradually reduce over a long period of time, with the epidemic reaching low levels in late 2020, but continuing out to the second half of 2021 - ICU and hospital occupancy stabilizes and gradually decreases, thus providing a necessary level of protection for the health service.
Limitations	- Sensitivity analysis shows that the effectiveness of any age-specific intervention policy is critically dependent upon the precise role of asymptomatic individuals in the epidemic - Data informing contact structure for the UK were measured historically - Assumed that mixing patterns would return to their pre-pandemic norm - Estimates of deaths resulting from an individual strategy does not take into account the potential for increased deaths due to exceeding hospital or ICU capacities, and so may underestimate deaths from strategies resulting in high occupancies - Though there have been recorded instances of super spreading events for COVID-19, model does not explicitly account for such dynamics		
Conclusions	Work provides strong evidence to support the need for a cautious, measured approach to relaxation, in order to provide necessary support for the health service and to protect the most vulnerable members of society		
Reference: Bollon J, Paganini M, Nava CR, De Vita N, Vaschetto R, Ragazzoni L, Della Corte F, Barone-Adesi F. Predicted Effects of Stopping COVID-19 Lockdown on Italian Hospital Demand. Disaster Medicine and Public Health Preparedness. 2020 May 18:1-5. https://www.cambridge.org/core/services/aop-cambridge-core/content/view/760FB1159CF65A60C36C401DF2955F02/S1935789320001573a.pdf/predicted_effects_of_stopping_covid19_lockdown_on_italian_hospital_demand.pdf			*Jurisdiction:* Italy
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/ Scenarios**	**Results**
Used a compartmental model to predict hospital	Assumptions:	Scenario A “intermittent lockdown”:	- The assumed increase in the number of infected is predicted to translate into a rise in

demand associated with the COVID-19 pandemic. Specifically, the model was used to evaluate two scenarios: A) an intermittent lockdown; B) a gradual relaxation of the lockdown. Predicted intensive care unit (ICU) and non-ICU demand was compared with the peak in hospital bed utilization observed in April 2020. Not stratified by age. Forecasted the demand for hospital ICU and non-ICU beds for COVID-19 patients from May-September 2020 based on the observed number of infected individuals until April 17, 2020.	- Recovered individuals remained immune from re-infection for the duration of the pandemic - Individuals stopped to be infectious once they were admitted to hospital (i.e. did not model transmission within healthcare settings) Parameters: Current number of infected, ICU patients, non-ICU patients, dead and recovered in Italy from February 24th – March 24th The predicted numbers obtained from the Italian Civilian Protection website (training data set) and compared to those reported in academic literature and observed in University Hospital (Maggiore Hospital, Novara) – then compared with actual figures observed between March 24th – April 17th No NPI/social distancing details for assumptions/parameters	- April 18th-30th, pandemic follows same trend as previous 2 weeks with steady reduction of new infections (Rt = 0.9) - Hypothesized lockdown is lifted May 1-30th and starting May 31, a new lockdown is enforced until end of simulation (September 1), bringing Rt to original value of 0.9 - Lag time of 2 weeks included to account for COVID-19 incubation period and diagnostic delay after symptom onset - Evaluated changes in ICU and non-ICU demand - ICU and non-ICU needs compared with maximum hospital bed utilization for COVID-19 observed before April 17th	the demand of ICU and non-ICU beds at the beginning of June - Maximum demand of ICU and non-ICU beds will occur in the first weeks of July - ICU needs will remain below peak observed in April (61%), but number of non-ICU will substantially rise and will exceed the maximum demand recorded in the early phase of the pandemic (133%) - Second part of July, bed demand will decrease, non-ICU needs will remain high until end of August
		Scenario B "gradual relaxation of lockdown": - May 1st onwards the restrictive measures are progressively reduced over time – increased Rt by 0.1 every 30 days, up to value of 1.3 - Evaluated changes in ICU and non-ICU demand - ICU and non-ICU needs compared with maximum hospital bed utilization for COVID-19 observed before April 17th	- Rise in the demand of ICU and non-ICU beds will start to be evident in July and will progressively increase over the summer - At the end of August ICU and non-ICU demand will be 95% and 237% of the April peak - No reduction in both ICU and non-ICU demand is predicted during the time frame covered by the simulation
Limitations:	- Assumed that the trend of non-ICU and ICU admission rates in the next months will remain similar to what we observed so far		

	- Did not take into account the effect that the gradual depletion of susceptibles from the population would have on our estimates. - Uncertainty owing to assumptions required for SARS-CoV-2 parameters.
Conclusions:	- Results suggest that Italian hospital demand is likely to remain high in the next months if restrictions are reduced, which seems likely to occur. Given the cuts recently suffered by the Italian National Health System, planning for the next few months should consider an increase in healthcare resources to maintain surge capacity across the country. Available assets should be deployed to the most struggling parts of the country with a certain grade of flexibility over time, taking also into account the immunity status of the population.

Reference: Ngonghala CN, Iboi E, Eikenberry S, Scotch M, MacIntyre CR, Bonds MH, Gumel AB. Mathematical assessment of the impact of non-pharmaceutical interventions on curtailing the 2019 novel Coronavirus. Mathematical Biosciences. 2020 May 1:108364. https://www.sciencedirect.com/science/article/pii/S0025556420300560			*Jurisdiction:* New York, USA
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/ Scenarios**	**Results**
Designed and analyzed a novel Kermack-McKendrick-type mathematical model for the transmission dynamics and control of COVID-19 in a population; It incorporates features pertinent to COVID-19 transmission dynamics and control, and provides a realistic real-time assessment and estimate of the burden of the pandemic in the state of New York, in addition to assessing some of the main intervention strategies being implemented in state. Not stratified by age. Model simulations are conducted with real-time data and trends to forecast predicted outcomes between February and December 2020	Assumptions: - Homogeneity in the community contact rate - Half of the 80% of cases that show no or mild symptoms are asymptomatic - By April 2 2020, 40% reduction in baseline value of β has already been achieved in both NY state and nationwide Parameters: - Effective contact rate (measure of social distancing effectiveness) - Proportion of members of public who wear masks in public - Efficacy of face-masks to prevent acquisition of infection by susceptible individuals - Probability of infection per contact - Rate at which quarantined individuals revert to the susceptible class - Modification parameter for the assumed reduced infectiousness of asymptomatically infectious (hospitalized/isolated) humans - Efficacy of quarantine to prevent acquisition of infection during quarantine	Baseline - Simulated the model using baseline parameter values to assess the population-level impact of the various control and mitigation strategies against the spread of COVID-19 in NY - Simulated the model using the calibrated parameters (see Table 4) together with the baseline estimated parameters to assess the population-level impact of various control measures in the entire US.	- 66,300 patients in hospital (or in self-isolation) at the pandemic peak, expected to be attained on May 5, 2020 and 105,100 cumulative number of deaths for the NY state - For the entire US, under the baseline nation-wide social-distancing scenario, are 115,000 daily hospitalizations at the pandemic peak and 164,000 cumulative number of deaths - a social distancing regimen that reduces contact rate parameter by 10% from its baseline value, the expected number of daily hospitalizations/isolation of confirmed cases at the peak of the pandemic decreases to 50,380 (corresponding to a 24% decrease in hospitalizations/isolation from baseline) for the NY state - Nation-wide hospitalizations/isolation of confirmed cases at peak of pandemic decreases by 21% to 89,930 - Highly-effective social-distancing strategy (such as a social-distancing strategy that results in at least 40% reduction in the baseline value) - peak hospitalizations/isolation of confirmed cases for NY state and entire US dramatically reduce to 5,000 and 14,000, respectively

<table>
<tr>
<td rowspan="3"></td>
<td rowspan="3">- Incubation period for non-quarantined (quarantined) exposed individuals
- Rate at which asymptomatically-infectious humans are detected (via contact-tracing) and hospitalized/isolated
- Rate at which exposed non-quarantined individuals are detected (via contact-tracing) and placed in quarantine
- Proportion of exposed non-quarantined individuals who progress to the Iu(Ih) class at the end of the incubation period
- Proportion of exposed non-quarantined individuals who progress to the Ia class
- Recovery rate for individuals in the Iu(Ih)(Ia)(Iicu) class
- Disease-induced mortality rate for individuals in the Iu(Ih)(Ia)(Iicu) class
- Hospitalization rate of non-quarantined infectious individuals
- Proportion of exposed quarantined individuals who are hospitalized (not hospitalized) at end of the incubation period
- Efficacy of quarantine, hospitalization/isolation and ICU admission to prevent infected individuals in quarantine, hospital/isolation and ICU from transmitting infection
- **See Table 2.1 on p. 7 for parameters

NPI measures include:
- Temporary closure of schools/non-essential businesses</td>
<td></td>
<td>(this represents a 92% and 88% reduction in peak hospitalizations for the NY state and nationwide, respectively)
- Cumulative mortality for New York state and the entire US reduce, respectively, to 20, 700 and 59, 600</td>
</tr>
<tr>
<td>To assess the population-level impact of the duration and timing of when to terminate current strict social-distancing protocols in NY state and entire US</td>
<td>- Where current strict social distancing protocols assumed to be implemented right from beginning of COVID-19 pandemic in NY state (March 1, 2020) and the entire US (January 20, 2020) and maintained until early December, 2020, the results obtained for the cumulative mortality recorded for NY state and the entire US are 25, 000 and 60, 000, respectively - represents 76% and 63% reductions, respectively in comparison to the baseline scenario (i.e., worst-case scenario where social distancing/community contacts-reduction strategies have not been implemented at stringent levels
- Early termination of the current strict social-distancing measures (by the end of April 2020) will result in 144,000 deaths representing (37% increase from baseline) in NY and 156,000 deaths in US
- Measures terminated by the end of May, 2020 - the cumulative mortality figures are projected to be 91, 800 for NY state and 118, 300 for the entire US; this represents a 13% and 28% reduction, respectively, in baseline cumulative mortality. Finally, if social-distancing measures are terminated at end of June, 2020, the projection for the cumulative mortality figures are 33,200 for NY state and 50, 300 for the entire US, 68% and 69% reductions, respectively, in the baseline cumulative mortality</td>
</tr>
<tr>
<td>The effect of quarantine of individuals suspected of being exposed to COVID-19</td>
<td>- Quarantine of susceptible individuals has only marginal impact in reducing COVID-</td>
</tr>
</table>

	- Aversion of crowded events/mass gatherings - Moving in-person meetings to online, virtual, etc. - Face-mask usage in public spaces		related hospitalizations for both NY state and entire US - Implementation of perfect quarantine reduces hospitalizations to 60,000 (NY) and 97,000 (entire US) - Mass quarantine of suspected cases may not be a cost-effective public health strategy
		The effect of contact-tracing (measured in terms of the detection of asymptomatic cases, following testing/ diagnosis of a confirmed COVID-19 case they may have had close contacts with or random testing) on the transmission dynamics and control of the COVID-19 pandemic	- If implemented at its baseline rate, contact tracing reduces size of pandemic peak number of new COVID-19 cases by 27% for the state of NY, and by 22% nationwide, while a 75% improvement in contact-tracing will reduce the predicted number of confirmed cases to approx. 31, 300 for the state of NY and 41,200 nationwide
		Assess the population-level impact of the widespread use of masks in public, and assess the combined impact of public face-masks use strategy and strict social-distancing strategy	- Using an efficacious mask, such as a mask of efficacy 50%, can greatly flatten pandemic curve, in addition to significantly reducing the burden of the pandemic (measured, in this case, in terms of hospitalizations) - If 75% of the populace in NY or entire US wear masks with efficacy as low as 25% (i.e., cloths masks), the number of hospitalizations will be reduced by 63% and 64%, respectively - Combining strict social-distancing strategy with a strategy based on using moderately-effective face-masks in public, will lead to elimination of the disease in NY state if only 30% of the population use face-masks in public
Limitations:	- Limited to non-pharmaceutical interventions - Large uncertainty owing to the current limited knowledge around SARS-CoV-2 and the assumptions associated		
Conclusions:	In the case of the other Coronaviruses in the past (namely SARS and MERS), COVID-19 is a pandemic that appears to be controllable using basic non-pharmaceutical interventions, particularly social-distancing and the use of face-masks in public (especially when implemented in combinations).The factors that are obviously critically-important to the success of the anti-COVID-19 control efforts are the early implementation (and enhancement of effectiveness) of these intervention measures, and ensuring their high adherence/coverage in the community		

Reference: Tuite AR, Fisman DN, Greer AL. Mathematical modelling of COVID-19 transmission and mitigation strategies in the population of Ontario, Canada. CMAJ [Internet]. 2020a *UPDATE (letter):* Tuite AR, Greer AL, De Keninck S, et al. Risk for COVID-19 Resurgence Related to Duration and Effectiveness of Physical Distancing in Ontario, Canada. Ann Intern Med 2020b. doi: https://doi.org/10.7326/M20-2945			*Jurisdiction*: Ontario
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/ Scenarios**	**Results**
Age structured compartmental transmission dynamic model of COVID-19, to explore the potential impact of case-based and non-case-based non-pharmaceutical interventions in the population of Ontario, Canada, with a focus on ICU capacity -Modified 'Susceptible-Exposed-Infectious-Recovered' (SEIR) framework incorporating additional compartments to account for public health interventions, different severities of clinical symptoms, and hospitalization risk -Analysis focuses on identifying strategies that keep the number of projected severe cases (hospital and ICU admissions) within a range that would not overwhelm the Ontario health care system, while also considering the amount of	Parameters include: - latent period -pre-symptomatic infectious period -infectious period (mild/moderate) -infectious period (severe) -basic reproduction number -time in quarantine -relative risk of transmission for case in isolation -average hospital LOS for case not requiring ICU care -average hospital LOS pre-ICU admission -average ICU LOS -average hospital LOS post-ICU - probability of severe infection (stratified by age group and presence of comorbidities -probability severe case requires ICU admission -probability of death in cases admitted to ICU (stratified by age group and presence of comorbidities) -natural history and clinical course of infection were derived from published studies Assumptions: -some degree of testing and isolation was in place for the base model -all deaths occurred in cases requiring intensive care -isolated cases were assumed to have reduced transmission compared to non-isolated cases	Base model (limited testing, isolation and quarantine; assumed a degree of testing and isolation was occurring and a proportion of exposed cases were quarantined)	In the model base case, with limited testing, isolation and quarantine, it is estimated that 56% (95% CrI: 42-63%) of the Ontario population would be infected over the course of the epidemic (this would include cases of all severities) Highest attack rates in those aged: - 5-14 years (77%, 95% CrI: 63-83%) - 15-49 years (63%, 95%CrI: 48-71) Lowest attack rates in those aged: - 5 years (50%, 95% CrI: 37-58%) - 50-69 years (47%, 95% - >70 years (30%, 95% CrI: 21-36) At the peak of the epidemic, in the absence of any resource constraints to provide care (i.e., assuming all cases requiring medical care receive it), the model projected 107,000 (95% CrI: 60,760-49,000) cases in hospital and 55,500 (95% CrI: 32,700-75,200) cases in ICU. The high prevalence of cases in ICU reflects the mean ICU LOS associated with COVID-19 infection in other countries.
		Fixed duration intervention: (i) enhanced testing and contact tracing (ii) restrictive social distancing measures (iii) a combination of enhanced testing and contract tracing, along with less restrictive social distancing than in (ii)	All of the interventions considered were projected to delay the epidemic peak and reduce the number of cases requiring ICU care at the peak Effectiveness of the interventions scaled with intervention duration

time these interventions would be in place. *Timeline*: 2-year time period	-social distancing measures reduce the number of contacts per day across the entire population -recovered individuals remain immune from reinfection for the duration of the epidemic. -individuals remained infectious until they recovered or were hospitalized (did not model transmission within healthcare settings) -The model was initiated with 750 prevalent cases (based on 150 reported cases in Ontario on March 19, 2020 and an assumed reporting rate of 20%), that were randomly distributed across the infectious compartments -included cases in hospital and requiring intensive care to estimate health care requirements over the course of the epidemic -added volatility to the transmission term to capture variability Assumption that physical distancing would lead to 70% reduction in contacts		• intervention duration ≤6 months: no appreciable difference on final attack rate • intervention duration 12 and 18 months of heightened response measures: proportion of the population infected at the end of the 2-year period was reduced and, in some simulations, the prevalence of cases requiring intensive care fell below Ontario's current capacity for all or part of the time period • largest effect: restrictive social distancing intervention (ii) • combination intervention was projected to substantially reduce attack rates when implemented for 18 months, while enhanced case detection in the absence of social distancing measures had a more modest effect, on average Substantial variability in model projections, due to model stochasticity
		Dynamic intervention (interventions turn on/off based on # cases requiring ICU care in the population): (i) enhanced testing and contact tracing (ii) restrictive social distancing measures (iii) a combination of enhanced testing and contract tracing, along with less restrictive social distancing than in (ii) - 200 COVID-19 cases in the ICU (across Ontario) as a threshold for turning the intervention on, based on ~50% saturation of available beds combined with the recognition that	- Dynamic interventions were projected to be effective for reducing the proportion of the population infected at the end of the two-year period, with potentially shorter durations of social distancing than the fixed duration approach (e.g. when implemented dynamically, 13 months of social distancing, cycled on and off, reduced the mean overall attack rate to 2%) For the social distancing alone and combination intervention scenarios, observed atypical epidemic curves, with the number of cases increasing and decreasing repeatedly over time. In these scenarios, the median number of cases in ICU was reduced below current estimates of Ontario's ICU capacity.

		there is a lag between cases acquiring infection and requiring intensive care, such that one would expect ICU needs to grow rapidly once initial COVID-19 cases present for care	
Update: Letter published in Ann Intern Med (27 May 2020)	- Calibrated model to observed Ontario data (March 19-May 3, 2020) using maximum likelihood estimation, incorporated recent data on durations of latent and presymptomatic periods and revised values for the proportion of mild infections that were detected and isolated (10%) and the proportion of exposed cases that were quarantined (10%) based on data from local public health partners and other modeling groups. - Assumed a 70% reduction in contacts with the implementation of physical distancing measures approximately 3 weeks after the model start date of 6 March 2020. - Fitting involved varying the basic reproductive number (R_0), initial number of infected persons, infectious period, and average length of ICU stay, with all other parameters unchanged.	Same as original study	- Model projected up to 37.4 cases (95% credible interval [CrI], 27.7 to 59.4 cases) in ICUs per 100,000 persons in the population *without* intervention, compared *with* 2.0 cases (95% CrI, 1.6 to 2.3 cases) per 100,000 with physical distancing. - Deaths among hospitalized case patients *without* intervention (12.7 deaths [95% CrI, 9.9 to 18.7 deaths] per 100,000) were 5-fold higher than *with* physical distancing (2.5 deaths [95% CrI, 2.0 to 2.9 deaths] per 100,000) - Relaxation of physical distancing measures without compensatory increases in case detection, isolation, and contact tracing was projected to result in a resurgence of disease activity - Lifting restriction after 8 weeks results in estimates that at 50% of normal social contact ICU capacity would be exceeded within 55 days - Projections remain within ICU capacity when 70% of normal social contact remains in place
Limitations:	- does not include within-hospital transmission cycles in this model iteration - at time of writing, limitations in testing capacity in Ontario, and lack of information on ICU occupancy by COVID-19 patients - not attempted to model social distancing measures in a highly realistic way, but rather generically as reductions in contact frequency - does not include seasonality - - does not model the fact that that abrupt surges in death resulting from full ICUs would result in lower demands for ICU beds		
Conclusion:	- This study uses an age structured compartmental transmission dynamic model (SEIR) of COVID-19 in Ontario, focusing on ICU resource capacity. Significant public health measures are required in order to slow COVID-19 cases from overwhelming ICU capacity, a finding consistent with other COVID-19 models and that aligns with experiences in Italy and Spain. Dynamic		

	social distancing that is responsible to ICU bed capacity is projected to support maintaining capacity of the health system and potentially allow for periodic relief for the economy.

Note: Data in tables extracted directly from articles

Table 2. Additional Modelling Studies with Short-Term Projections

Reference			*Jurisdiction*
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/ Scenarios**	**Results**
Limitations			
Conclusion			
Reference: Los Alamos National Laboratory: COVID-19 Confirmed and Forecasted Case Data https://covid-19.bsvgateway.org/			All US states, and Global forecasts
Model forecasts the number of future confirmed cases and deaths as reported by John Hopkins University (JHU) Coronavirus Resource Center dashboard. Model has two processes: one, to model how the number of COVID-19 infections changes over time; two, maps the number of infections to the reported data Timing: Model can be used to produce short-and-long-term forecasts; short-term = one week; long-term = six weeks; forecasts are updated each Monday and Thursday, incorporating latest data Not stratified by age. Note: model can be filtered and applied to Canada and is updated regularly as data becomes available	Assumptions: - There is a ~60% maximum cap on the number of individuals who could eventually be confirmed cases, with the cap being drawn from a distribution - determined this cap using an overall unmitigated attack rate of 50-70% - The growth rate of COVID-19 will go down over time as a result of interventions, but do not explicitly model - A fraction of the newly generated cases will die and learn that fraction from observations - Assume a persistence model, which models the case fatality fraction parameter tomorrow equal to the case fatality fraction parameter today: the model assumes that the case fatality fraction is consistent over the length of the forecast period and for those cases that result in a death, we make the simplifying assumption that they happen in synchrony with receiving a confirmed positive test when in reality, there is a non-zero period of time between the time of	Not applicable	Canada: As of 2020-05-20, Canada has recorded 81,575 confirmed cases and 6,150 deaths Over the past week, the total number of confirmed cases has been increasing by an average of 1.5% per day, or 1,144 confirmed cases a day Over the past week, the total number of deaths has been increasing by an average of 1.8% per day In one week from 2020-05-20, the model forecasts about 88,600 total confirmed cases (90% Prediction Interval: 85,500 - 93,000) In one week from 2020-05-20, the model forecasts about 6,900 total deaths (90% Prediction Interval: 6,500 - 7,400) At the 95th percentile (a worst case forecast) that there could be as many as 93,000 confirmed cases (1.9% average daily growth rate). At the 5th percentile (a best case forecast), there could be 85,500 confirmed cases (0.67% average daily growth rate) At the 95th percentile that there could be as many as 7,400 deaths. At the 5th percentile, there could be 6,500 deaths

	positive testing and the time of death - For every day in the model, assume that the number of underlying confirmed cases in a state informs a distribution of possible reported confirmed cases/deaths parameterized with the mean equal to the underlying number of cases/deaths from the infection process - In general that the growth will decrease over time - the growth rate will decrease on average about once every seven days, reflecting realized efforts, such as social distancing, to reduce the growth rate Parameters: - Growth rate (can probabilistically decrease (common), increase (rare), or stay the same (most common)) - Case fatality fraction (to model new deaths, fraction of the new generated cases will die) Growth rate determined by NPIs such as social distancing and thorough handwashing		The Middle Case (50th percentile) forecast has most closely tracked with observations of cases and deaths in Canada- Model scenario that has most often had the smallest mean absolute percent error in forecasting cases for Canada By 2020-07-01, the model forecasts about 111,000 total confirmed cases (90% Prediction Interval: 94,400 - 152,000) By 2020-07-01, the model forecasts about 9,200 total deaths (90% Prediction Interval: 7,500 - 13,400) The largest single day increase in confirmed cases in Canada based on data as of 2020-05-20 occurred on 2020-04-05 and was 2,778 confirmed cases There is a ~96% chance that the peak (i.e., the maximum number of new daily confirmed cases) has occurred in Canada
Limitations	- The number of confirmed cases and deaths is an underestimate for the actual number of COVID-19 cases/ deaths - The model produces forecasts, not projections; meaning it does not explicitly model the effects of interventions or other "what-if" scenarios - The model forecasts are probabilistic. There is a high degree of uncertainty in future trajectories, given the possibilities of changing intervention strategies, changing case definitions, and changing rates of testing		
Conclusion	- This interactive case data model forecasts the number of future confirmed cases and deaths using data from John Hopkins University (JHU) Coronavirus Resource Center dashboard for all US states and Global jurisdictions over a 1-6 week period		

<table>
<tr><td colspan="3">Reference: Yamana T, Pei S, Kandula S, Shaman J. Projection of COVID-19 Cases and Deaths in the US as Individual States Re-open May 4,2020. medRxiv [Internet]. 2020 Available from:http://medrxiv.org/content/early/2020/05/13/2020.05.04.20090670.abstract</td><td>Jurisdiction: United States</td></tr>
<tr><td>Purpose and Timeline</td><td>Assumptions and Parameters</td><td>Interventions/ Scenarios</td><td>Results</td></tr>
<tr><td rowspan="3">Project the effects of week increases of transmissibility, relative to current estimates of effective reproduction number, R_t, on COVID-19 outcomes over course of 6 weeks in the United States. The model represents two types of movement: daily work commuting and random movement. Information on county-to-county work commuting is publicly available from the US Census Bureau2, which is used to determine rates of intercounty movement prior to March 15, 2020. Used the age-stratified infection fatality rate (IFR).

Three control scenarios to account for increases in contact rates due to loosening restrictions in states that have begun to reopen are presented.

Timeline: Projections are generated using a county-scale metapopulation model optimized to daily confirmed COVID-19 cases and deaths from February 21 – May 2, 2020</td><td rowspan="3">Assumptions:
- the number of random visitors between two counties is proportional to the average number of commuters between them
- daytime transmission lasts for 8 hours and nighttime transmission lasts for 16 hours
- average reporting delay of 8 days
- reporting rate of 1/6=16.7%

Parameters:
- reproductive number
- daily work commuting
- random movement
- intra-county movement
- inter-county movement
- daytime transmission
- nighttime transmission

Person-person contact reduced/reintroduced via strong social distancing practices in stores, restaurants, theatres, as well as increased use of face-masks
*model does not differentiate between types of businesses/activities, nor differentiation between states in contact reintroduction interventions</td><td>Weekly 20% decrease in places with growing weekly cases and a one-time 10% increase in places with return to work (latter supersedes the former)</td><td>- Increasing contact rates in reopening states resulted in a rebound in COVID-19 incidence, hospitalizations, and deaths at the national scale
- With few exceptions, reopening states are projected to experience exponential growth of both cases and deaths
- States with restrictions remaining in place are projected to have decreasing or stable numbers of cases and death</td></tr>
<tr><td>Weekly 20% decrease in places with growing weekly cases and a weekly 10% increase in places with return to work (latter supersedes the former)</td><td>- Increasing contact rates in reopening states resulted in a rebound in COVID-19 incidence, hospitalizations, and deaths at the national scale
- Rebound was faster and stronger for the weekly-increase scenario
- With few exceptions, reopening states are projected to experience exponential growth of both cases and deaths
- States with restrictions remaining in place are projected to have decreasing or stable numbers of cases and death</td></tr>
<tr><td>Weekly 20% decrease in places with growing weekly cases</td><td>- Increase in cases and deaths is not apparent at the national scale until two to four weeks after the first states begin to reopen
- With few exceptions, reopening states are projected to experience exponential growth of both cases and deaths
- States with restrictions remaining in place are projected to have decreasing or stable numbers of cases and death</td></tr>
<tr><td>Limitations</td><td colspan="3">- Model is optimized using observations through May 2, 2020; however, those observations, i.e. confirmed cases and deaths by county, represent infections that were acquired by individuals 1-3 weeks earlier - effects of changes in social distancing and contact patterns over the last 3 weeks on virus transmission have yet to be fully observed</td></tr>
</table>

	- Landscape to which this model has been optimized is highly variable in space and time, due to differences in contact behavior, population density, control measures and testing practices - Response to COVID-19 transmission will be adaptive at both the government and the individual level – plausible restrictions on contacts with increase in case incidence will be put into place to counter presented trajectory, impacting presented projections
Conclusion	- The findings presented from model simulation indicate a rebound in COVID-19 incidence and deaths beginning in late May 2020, approximately 2-4 weeks after states being to open, with variability according to the three simulated scenarios based on different levels of individuals' contact and movement. Notably, lag between infection attainment and reported case confirmation, combined with inadequate comprehensive, large-scale testing and contact tracing, will disguise potential rebound and/or exponential growth of COVID-19 until it has significantly progressed.

Reference: Joel R Koo, Alex R Cook, Minah Park, Yinxiaohe Sun, Haoyang Sun, Jue Tao Lim, Clarence Tam, Borame L Dickens. Interventions to mitigate early spread of SARS-CoV-2 in Singapore: a modelling study. Lancet Infect Dis 2020. https://doi.org/10.1016/S1473-3099(20)30162-6			***Jurisdiction:*** Singapore
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/Scenarios**	**Results**
To develop a national spatial model of COVID-19 transmission in Singapore to estimate the distribution of cases across time and space and to assess the potential impact of interventions on outbreak size should local containment efforts fail Epidemic simulation model - FluTE,15 an agent-based influenza epidemic simulation model, accounts for demography, host movement, and social contact rates in workplaces, schools, and homes to estimate the likelihood of human-to-human transmission of SARS-CoV-2 should local containment fail. Age demographic data informed projection. Ran models for 80 days (from mid-March) to investigate the early stages of an epidemic and seeded 100 local	Assumptions: - no individuals had immunity to SARS-CoV-2 - used SARS-CoV-2 parameters to estimate infectivity - how infectious an individual is over time - proportion of asymptomatic case in the population assumed at 7.5% - cumulative distribution function for the mean incubation period (with SARS-CoV and SARS-CoV-2 having the same mean incubation period of 5·3 days) and the duration of hospital stay after symptom onset (3·5 days) - Asymptomatic individuals able to infect at a 50% reduced rate compared with symptomatic counterparts Parameters:	Baseline scenario (i.e., no interventions) - ran 1000 epidemic simulations to account for the stochasticity in infection contact networks and to calculate CIs across time	- R_0=1·5, the median cumulative number of infections on day 80 was 279,000 (IQR 245,000–320,000), which corresponds to 7·4% (IQR 6.5, 8.5) of the population - Day 80, when R_0 was 1.5, around 279,000 individuals would be infected, when R_0 was 2.0, around 727,000 individuals would be infected, and when R_0 was 2.5, around 1,207,000 individuals would be infected.
		Isolation of infected individuals and quarantine of their family members ("Quarantine")	- Reduced the median cumulative number of infections at day 80 to 15,000 (IQR: 800–30,000), which is a 94·8% decrease (IQR: 90.2, 99.7) in the number of infected individuals compared with the baseline scenario.
		Quarantine plus immediate school closure for 2 weeks	- Reduced the median cumulative number of infections on day 80 to 10,000 (IQR:200–28,000)
		Quarantine plus immediate workplace distancing, in which 50% of the workforce is encouraged to work from home for 2 weeks	- Reduced the median cumulative number of infections on day 80 to 4,000 (IQR: 200–23,000).

cases randomly among the resident population at 0 days, representing a few generations of local transmission at the time of scenario implementation (i.e., when contact tracing has failed to identify cases within the community and unknown local transmission has started).	- Three values for the basic reproduction number (R0) chosen for the infectiousness factor (1·5, 2·0, and 2·5) on the basis of analyses of Wuhan case data by Wu and colleagues NPIs (based on standard interventions for respiratory virus control): - Isolation of infected individuals, quarantine of their family members - Immediate school closure (minimum of 2 weeks) - Workplace distancing, where % of workplace encouraged to work remotely from home (50% in this model)	Combination of quarantine, immediate school closure, and workplace distancing (combined intervention)	- Decreased the median cumulative infection count on day 80 to 1,800 (200–23,000), representing a 99·3% (IQR: 92.6, 99.9) reduction from the baseline scenario
Limitations	- Errors exist in estimations of population features that are based on data that have been sample enumerated - Epidemiological characteristics of COVID-19 remain uncertain in terms of the transmission and infectivity profile of the virus - The contact patterns between individuals are highly dynamic and heterogeneous across the population - Effectiveness of the interventions might vary depending on the ongoing seeding of imported cases, which was not accounted for - Challenging accounting for multiple unseen factors at the time of writing (e.g., infection rates at mass gathering, contact events such as public transit, delay in quarantine, etc)		
Conclusions	- In the event that local containment is unsuccessful, findings suggest that national outbreak control is feasible provided that R_0 is low (≤1·5), with a combination of the proposed intervention measures (quarantine, school closure, and workplace distancing) being most effective. - Especially for lower infection scenarios (R_0 of 1.5), a combined approach comprising quarantine (for infected individuals and their families), school closure, and workplace distancing is effective and could prevent 99.3% of infections (IQR 92·6–99·9) when compared with the baseline scenario. - At higher infectivity scenarios, outbreak prevention becomes considerably more challenging because although effective, transmission events still occur. - Combined interventions should be implemented rapidly upon confirmation of second-generation local transmission occurring within the resident population to suppress increases in the national R_0.		
Reference: Dehning J, Zierenberg J, Spitzner FP, Wibral M, Neto JP, Wilczek M, et al. Inferring change points in the spread of COVID-19 reveals the effectiveness of interventions. Science [Internet]. 2020			***Jurisdiction:*** Germany
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/Scenarios**	**Results**

Susceptible-Infected-Recovered (SIR) model to provide time-critical information for crisis mitigation: (i) establishing central epidemiological parameters, such as the basic reproduction number, that can be used for short-term forecasting; (ii) simulating the effects of different possible interventions aimed at the mitigation of the outbreak; (iii) estimating the actual effects of the measures taken not only to make rapid adjustments but also to adapt short-term forecasts. Combine the SIR model (and generalizations thereof) with Bayesian parameter inference and augment the model by a time-dependent spreading rate. Not stratified by age. Models case # out to May 3; and 21 days for impact of intervention from date of initiation	Assumptions: - None stated Parameters: -Spreading rate -Recovery rate -Effective spreading rate -Spreading rate after *i*-th intervention -Time of *i*-th intervention -Amplitude of weekend corrections -Phase shift of weekend correction -Scale factor of the width of Student's t-distribution -Reporting delay	None - No social distancing; public behaviour unaltered	- Spread continues with the inferred rate (median=0.41)
		Mild - Mild social distancing	- The spreading rate decreases to 50% (median=0.21) - Although people effectively reduce the number of contacts by a factor of two, the total number of reported cases continues to grow alongside this scenario for the time period of the reporting delay (median *D*=8.6; D=8.6 from initial phase) - Still observe an exponential increase of new infections after the intervention becomes effective, because the growth rate remains positive.
		Severe - Strong social distancing	- The spreading rate decreases to 10% (median=0.04). - Contacts are severely limited, but even when people stay at home as much as possible, some contacts are still unavoidable. - No effect is visible until the reporting delay is over. Thereafter, a quick decrease in daily new infections manifests within two weeks (delay plus change point duration), and the total number of cases reaches a stable plateau. - Only in this last phase is a plateau reached, because here the growth rate becomes negative, which leads to decreasing numbers of new infections.
Limitations	- Since change point detection entails evaluating models with different numbers of parameters, some form of fair model comparison is needed; however, there is insufficient out-of-sample data to do so in the early stage of the outbreak.		
Conclusions	- This Bayesian approach allows detection and quantification of the effect of governmental interventions and, combined with potential subsequent interventions, forecasting future case number scenarios - Results highlights the importance of precise timing and magnitude of interventions for future case numbers, and stresses the importance of including the reporting delay D between the date of infection and the date of the confirmed case in the model.		

	- Reporting delay, D, together with the time required to implement interventions means that changes in our behavior today can only be detected in confirmed cases in two weeks' time. Thus, this delay, combined with a current spreading rate that is still close to zero, indicates extremely careful planning of future measures is essential.		
Reference: Firth JA, Hellewell J, Klepac P, et al. Combining fine-scale social contact data with epidemic modelling reveals interactions between contact tracing, quarantine, testing and physical distancing for controlling COVID-19. CMMID nCov working group.2020. https://cmmid.github.io/topics/covid19/tracing-network-local.html Accessed May 26, 2020.			***Jurisdiction:*** UK
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/Scenarios**	**Results**
To develop, refine and apply an epidemic model which simulates COVID-19 outbreaks using Haslemere (Surrey, UK) network data to examine the effects of various control measures (i.e., testing, physical distancing, quarantine, contact tracing), and how implementation of these measures (independently and interactively) could impact COVID-19 incidence and outbreak. Model is age-structured. Timeline: Each simulation ran for 70 days, at which point the majority of new infections came from outside the network, with all scenarios replicated 1000 times.	Assumptions: - Structure of fine-scale social networks - Susceptible contacts are traced with a given probability (0.4-0.8 tested) - Probability of tracing constant over time; independent of previous isolation/quarantine events - 20% of contact tracing attempts missed - 40%, 60%, 80% contacts traced - Short delay between isolation/quarantine and testing - Individuals isolate independently of previous notifications/isolations - 100% adherence to quarantine among traced contacts - Incubation period 5.8 days - 1 day (0.4-1.9) days ('short') delay from onset/tracing to isolation, isolation to testing - 3.5 days (2.8-5.2) days ('medium') delay from onset/tracing to isolation, isolation to testing - 50% infectiousness of asymptomatic individuals - Outside infection rate 0.0001, 0.001, 0.005, 0.01	- Used null networks to understand the network properties that shape predictions of COVID-19 spread under different control scenarios - Four null network scenarios with 1000 networks generated under each of these; 'edge null' (random social associates), 'degree null' (individual differences in sociality, but random social links between dyads), 'lattice null' (triadic and tight clique associations) and 'cluster null' (ring structure only between individuals observed as connected [at least 1 social link] in network). - With null networks and population-level physical distancing scenarios, ran one replicate simulation on each of the 1000 simulated networks	- Scenarios with no control measures quickly led to substantial numbers of infections - Contact tracing scenarios reduced the number of infections but resulted in a large number of contained cases in early-mid outbreak stages - Uncontrolled outbreaks in the Haslemere network stemming from a single infected individual resulted in a median of 12% (IQR = 9.4%-15.8%) of the population infected after 70 days - Secondary contact tracing resulted in the largest reduction (7.3%, 6.4%-8.3%) of the population infected after 70 days. The number of quarantined individuals was very high under both primary and secondary contact tracing, with a median of 29% (IQR = 19%-40%) of the population quarantined during the outbreak peak with the latter - Interventions reduced overall size of outbreaks and case growth rate - Outbreak size decreased with percentage of contacts traced in all scenarios, and increased with reproduction number, proportion of asymptomatic cases, proportion of pre-onset transmission, delay between onset/tracing and isolation/quarantine, and number of initial cases. - High levels of testing led to a substantial reduction in the number of quarantined cases in both primary and secondary contact tracing scenarios, with on average 1.7%

	Parameters: - Incubation period - Serial interval - Delay from onset/tracing to isolation, and from isolation to testing - Initial cases - Scaling parameter (and corresponding reproduction number (R0) - Percentage asymptomatic individuals - Infectiousness of asymptomatic individuals - Percentage individuals infectious pre-onset - Outside infection rate - Percentage of contacts traced - Maximum number of tests - Test false positive rate - Test false negative rate		(0.7%-3.3%) and 11.7% (6%-22%) quarantined cases during the outbreak peaks, respectively, when testing capacity was 50 tests per day - Number of tests required to reduce number of quarantined cases large - Across control scenarios, physical distancing led to only a small reduction in the number of overall cases
Limitations	- Social network taken from a single, small town and over a short period of time; do not know to what extent the social dynamics will be applicable to larger cities and other contexts and over long periods - Haslemere data does not sample the entire population and children under the age of 13 not included in the experiment Could potentially have an impact on outbreak and social tracking dynamics		
Conclusion	The use of epidemic modelling to simulate COVID-19 spread on real-world networks at a local level, while including the associated impact of control measures and physical distancing strategies, illustrates how specific non-pharmaceutical interventions (i.e., contact tracing) can help to slow the spread and reduce incidence of COVID-19 in a population.		
Reference: IHME COVID-19 Health Service Utilization Forecasting Team. Forecasting the impact of the first wave of the COVID-19 pandemic on hospital demand and deaths for the USA and European economic area countries.medRxiv.2020. https://doi.org/10.1101/2020.04.21.20074732 Accessed May 26, 2020.			***Jurisdiction:*** All USA states and EEA countries discussed in pre-print. NOTE: Results column presents data for Canada as this is now available on interactive tool.
Purpose and Timeline	**Assumptions and Parameters**	**Interventions/Scenarios**	**Results**

A multi-stage hybrid model. Modeling approach involves estimating COVID-19 deaths and infections, as well as viral transmission, in multiple stages. It leverages a hybrid modeling approach through its statistical component (deaths model), a component quantifying the rates at which individuals move from being susceptible to exposed, then infected, and then recovered (known as SEIR), and the existing microsimulation component that estimates hospitalizations. Authors built this modeling platform to: (1) generate predictions of COVID-19 deaths and infections for all currently included locations; and (2) enable alternative scenarios on the basis of different levels of temperature, the percentage of populations living in dense areas, testing per capita, and social distancing approximated by changes in human mobility. This is particularly important as many locations ease or end prior distancing policies without having a clear sense of how these actions could potentially affect COVID-19 trajectories given current trends in testing and mobility, among others. IHME's new modeling framework, aims to provide a venue through which different COVID-19	Assumptions: - Social distancing efforts will continue until deaths reach a very low level - For modeling purposes, if mobility declined by 40% or more, any social distancing mandates that had yet to be formally implemented were considered in place at present. If mobility reductions had yet to reach 40%, our model assumption is that they would be implemented three weeks from the current date of estimation. - Modeling approach acts across the overall population (i.e., no assumed age structure for transmission dynamics), and each location is modeled independently of the others (i.e., we do not account for potential movement between locations). Parameters: - CurveFitModel. CurveFit supports parametrized curves that can be fit to data, modeling parameters using covariates, and post-processing, such as fitting linear combinations of CurveFit models. - Focus on parametric and semi-parametric inference in contrast to fully non parametric inference - Data on licensed bed and ICU capacity and average annual utilization by location obtained from a variety of sources for	Not applicable	See Interactive Tool for: Daily Infections and Testing: Estimated infections are the number of people estimated to be infected with COVID-19 each day, including those not tested, or showing symptoms. This is calculated using the known relationship between deaths and infections and are estimated to the future projected deaths. Confirmed infections represent the reported cases of COVID-19 each day, with 3-day smoothing to account for delays in reporting. Canada: - Estimated Infections as of May 23, 2020: 5,631(4,052-7,913) - Confirmed Infections as of May 23, 2020: 1,152 - Estimated Infections as of August 1, 2020: 30 (4-105) - Daily Deaths (per 100,000) As of May 23, 2020 0.32; As of August 1, 2020 0.00 (0.00-0.01) - Total Deaths (per 100,000) As of August 4, 2020 25.80 (23.85-29.06) Hospital Resource Use (All beds, ICU beds, Invasive ventilators) The numbers for All beds needed and All beds available include ICU beds. All beds available is the total number of hospital beds available for COVID patients minus the average historical bed use. - All beds available as of May 24, 2020: 8,855 - All beds needed as of May 24, 2020: 2,883 (2,388-3,798)

epidemic scenarios and responses can be explored by location. Includes an age-standardized structure. Timing: estimates of predicted health service utilization and deaths due to COVID-19 by day through the end of August 2020 as of May 2020. Note: Interactive model can be filtered for Canada and is updated regularly as data becomes available.	most countries to estimate baseline capacities - Observed COVID-19 utilization data obtained for a range of countries and USA states providing information on inpatient and ICU use or imputed from available resources. - Other parameters sourced from the scientific literature and an analysis of available patient-level data. Age-specific data on the relative population death rate by age are available from China, Italy, South Korea, the USA, Netherlands, Sweden, and Germany and show a strong relationship with age The latest (May 4th, 2020) SEIR models also includes: Smoother daily death trends as model inputs Hospitalizations of COVID-19 patients as an additional leading indicator for estimating COVID19 deaths in the next eight days. Correcting reported cases to account for scaling up testing Expanding the range of multi-Gaussian distribution weights for predicting epidemic peaks and shapes		- All beds needed as of August 1, 2020: 14(0-55) ICU beds available is the total number of ICU beds available for COVID patients minus the average historical ICU bed use. - ICU beds available as of May 24, 2020: 759 - ICU beds needed as of May 24, 2020: 874 (746-1,111) - ICU beds needed as of August 1, 2020: 5(0-19) Invasive ventilators needed does not account for the number of ventilators available (ventilator capacity data are not available at this time). - Invasive ventilators needed as of May 24, 2020: 776 (651-1,005) - Invasive ventilators needed as of August 1, 2020: 4 (0-16)

	Incorporating changes in mobility in the absence of formally enacted social distancing policies Directly modeling of disease transmission as a function of changes in human mobility and its relationship to social distancing policies, as well as temperature, testing rates, and the proportion of populations that live in dense areas.		

Limitations	- Does not explicitly incorporate the effect of reduced quality of care due to stressed and overloaded health systems beyond what is captured in the data. - Assumes that the shape of the epidemic curve is reasonably symmetric, making tail of the distribution likely too low, and the confidence interval at the end of the epidemic too narrow. - May underestimate the trajectory of an outbreak. - Potentially less accurate in mapping healthcare utilization and ICU beds. These projections rely on mappings to the estimated mortality rate.
Conclusions	- These estimates can help inform the development and implementation of strategies to mitigate the gap of timing for peak need for hospital resource requirements (i.e. ICU care, ventilator use), including reducing non-COVID-19 demand for services and temporarily increasing system capacity.

Note: Data in tables extracted directly from articles

Table 3. Triggers from Modelling Studies

Reference	Jurisdiction	Purpose	Methods and Strength of Predictions	Triggers	Conclusion
Ferguson NM, Laydon D, Nedjati-Gilani G, et al on behalf of the Imperial College COVID-19 Response Team. Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand. Imperial College London (16-03-2020), doi: https://doi.org/10.25561/77482	UK (Great Britain specifically) and USA	To 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. Modified an individual-based simulation model developed to support pandemic influenza planning to explore scenarios for COVID-19 in GB. Authors state ethical and economic considerations are not considered here – instead focus on feasibly and the impact of each strategy on	Summary of NPI interventions considered: 1. Case isolation in home (CI) 2. Voluntary home quarantine (HQ) 3. Social distancing of those over 70 years of age (SDO) 4. Social distancing of entire population (SD) 5. Closure of schools and universities (PC) Mitigation and Suppression strategies for GB. Impact of different policy options on the total number of deaths seen in a 2-year period and peak demand for ICU beds. 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. Infection fatality rate (IFR) estimate based on literature and adjusted for non-uniform attack rate. Overall IFR= 0.9% (95% credible interval [CrI]: 0.4%, 1.4%). Report does not provide evidence on strength of predictions.	Triggers broken out by mitigation and suppression strategies Mitigation - aim to use NPIs (and vaccines or drugs, if available) not to interrupt transmission completely, but to reduce health impact of an epidemic Suppression- aim is to reduce the reproduction # (the average number of secondary cases each case generates), R, to below 1, hence to reduce case numbers to low levels or eliminate human-to-human transmission	Best mitigation 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. 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. 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
			Mitigation Scenarios CI = Case isolation in home	- Predicted relative impact on both deaths and ICU capacity of a range of single and combined NPIs applied nationally in GB for a 3-month period	

Reference	Jurisdiction	Purpose	Methods and Strength of Predictions	Triggers	Conclusion
		health system impact.	HQ = Voluntary home quarantine SDO70 = Social distancing of those over 70 years of age SD = Social distancing of entire population PC = Closure of schools and universities	based on triggers of between 100 and 3000 critical care cases. - % 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. Results given for R_0=2.4 and R_0=2.2. **Below are results for R_0=2.2 only.** Trigger of cumulative ICU cases per week: 100, 300, 1000, 3000 presented in paper **PEAK ICU BEDS** *Trigger = 100 cumulative ICU cases per week* PC: 23% CI: 35% CI _HQ: 57% CI_HQ_SD: 25% CI_SD: 39% CI_HQ_SD070: 69% PC_CI_HQ_SDO70: 48% *Trigger = 3000 cumulative ICU cases per week* PC: 18% CI: 35% CI_HQ: 57% CI_HQ_SD: 47% CI_SD: 68% CI_HQ_SD070: 69% PC_CI_HQ_SDO70: 75% **TOTAL DEATHS** *Trigger = 100 cumulative ICU cases per week*	prevents people going to work. 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. Given local epidemics are not perfectly synchronized, 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. Total deaths are reduced with lower "off" triggers; however, this also leads to longer periods during which social distancing is in place. Peak ICU demand and the proportion of time social distancing is in place are not affected by the choice of "off" trigger.

Reference	Jurisdiction	Purpose	Methods and Strength of Predictions	Triggers	Conclusion
				PC: 3% CI: 21% CI_HQ: 34% CI_HQ_SD: 9% CI_SD: 15% CI_HQ_SD070: 49% PC_CI_HQ_SDO70: 19% *Trigger = 3000 cumulative ICU cases per week* PC: 4% CI: 21% CI_HQ: 34% CI_HQ_SD: 15% CI_SD: 27% CI_HQ_SD070: 49% PC_CI_HQ_SDO70: 24%	Overall, 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.
			Suppression Scenarios Interventions are only initiated after weekly confirmed case incidence in ICU patients (a group of patients highly likely to be tested) exceeds a certain "on" threshold, and is relaxed when ICU case incidence falls below a certain "off" threshold Suppression Scenario 1 - 3 interventions (case isolation + home quarantine + social distancing) - "On trigger" and is suspended when weekly ICU cases drop to 25% of that trigger value. - R_0=2.0 CI = Case isolation in home	**TOTAL DEATHS:** *On Trigger = 60 weekly incidence ICU cases* Do nothing: 410,000 CI_HQ_SD: 47,000 *Off Trigger as proportion of on trigger* 0.25: 85,000 0.5: 85,000 0.75: 85,000 *On Trigger = 400 weekly incidence ICU cases* Do nothing: 410,000 CI_HQ_SD: 44,000 *Off Trigger as proportion of on trigger* 0.25: 98,000 0.5: 100,000 0.75: 100,000	

Reference	Jurisdiction	Purpose	Methods and Strength of Predictions	Triggers	Conclusion
			HQ = Voluntary home quarantine SD = Social distancing of entire population	**PEAK ICU BEDS:** *On Trigger = 60 weekly incidence ICU cases* Do nothing: 130,000 CI_HQ_SD: 3,300 Proportion of time with SD in place: 96% *On Trigger = 400 weekly incidence ICU cases* Do nothing: 130,000 CI_HQ_SD: 3,800 Proportion of time with SD in place: 94%	
			Suppression Scenario 2 - 3 interventions (school/university closure + case isolation + social distancing) - "On trigger" and is suspended when weekly ICU cases drop to 25% of that trigger value. - R_0=2.0 CI = Case isolation in home SD = Social distancing of entire population PC = Closure of schools and universities	**TOTAL DEATHS:** On Trigger = *60 weekly incidence ICU cases* Do nothing: 410,000 PC_CI_SD: 6,400 *Off Trigger as proportion of on trigger* 0.25: 12,000 0.5: 15,000 0.75: 14,000 *On Trigger = 400 weekly incidence ICU cases* Do nothing: 410,000 PC_CI_SD: 30,000 *Off Trigger as proportion of on trigger* 0.25: 53,000 0.5: 61,000 0.75: 65,000 **PEAK ICU BEDS:** *Trigger= 60 weekly incidence ICU cases* Do nothing: 130,000 PC_CI_SD: 930 Proportion of time with SD in place: 69%	

Reference	Jurisdiction	Purpose	Methods and Strength of Predictions	Triggers	Conclusion
				Trigger = 400 weekly incidence ICU cases Do nothing: 130,000 PC_CI_SD: 2,900 Proportion of time with SD in place: 63%	
			Suppression Scenario 3 - 4 interventions (home quarantine + school/university closure + case isolation + social distancing) - "On trigger" and is suspended when weekly ICU cases drop to 25% of that trigger value. - R_0=2.0 CI = Case isolation in home HQ = Voluntary home quarantine SD = Social distancing of entire population PC = Closure of schools and universities	**TOTAL DEATHS:** *On Trigger = 60 weekly incidence ICU cases* Do nothing: 410,00 PC_CI_HQ_SD: 5,600 *Off Trigger as proportion of on trigger* 0.25: 8,700 0.5: 10,000 0.75: 11,000 *On Trigger = 400 weekly incidence ICU cases* Do nothing: 410,00 PC_CI_HQ_SD: 26,000 *Off Trigger as proportion of on trigger* 0.25: 39,000 0.5: 46,000 0.75: 51,000 **PEAK ICU BEDS:** *On Trigger = 60 weekly incidence ICU cases* Do nothing: 130,000 PC_CI_HQ_SD: 920 Proportion of time with SD in place: 58% *On Trigger = 400 weekly incidence ICU cases* Do nothing: 130,000 PC_CI__HQ_SD: 2,700	

Reference	Jurisdiction	Purpose	Methods and Strength of Predictions	Triggers	Conclusion
				Proportion of time with SD in place: 55% **See paper for more Triggers and R_0 scenarios**	
Davies NG, Kucharski AJ, Eggo RM, Gimma A, CMMID COVID-19 Working Group, Edmunds JW. The effect of non-pharmaceutical interventions on COVID-19 cases, deaths and demand for hospital services in the UK: a modelling study. medRvix [preprint]. doi: https://doi.org/10.1101/2020.04.01.20049908	UK - England, Wales, Scotland, and Northern Ireland	To use a stochastic age-structured transmission model to explore a range of intervention scenarios, including the introduction of school closures, social distancing, shielding of elderly groups, self-isolation of symptomatic cases, and extreme “lockdown”-type restrictions. Authors simulated different durations of interventions and triggers for introduction, as well as combinations of interventions. Each scenario, includes	Intensive Interventions including a significant program of social distancing, with a particular impact on leisure activities; workers being asked to work from home where possible; shielding of both elderly (70+) individuals and people in high-risk-groups of all ages; school closures; and self-isolation of symptomatic individuals. Does not appear to provide evidence on the reliability of triggers.	Results for the impact of longer-term and repeated interventions presented here. See paper for shorter 12-week intervention impacts. Median and 95% prediction interval reported. - Total Cases: 11M (6.6M-21M) - Total Deaths: 130K (73M-270M) - Cases in Peak Week: 820K (330K-3.2M) - Deaths in Peak Week: 9.3K (3.5K-40K) - Peak ICU beds required: 33K (12K-140K) - Peak non-ICU beds required: 62K (23K-270K) - Time to peak cases (weeks) 19 (9.2-66) - Proportion of time spent in lockdown (29-Jan 2020 to 31-Dec 2021: N/A - Total Infected: 28M (18M-48M)	Projected that triggering interventions locally instead of nationally could modestly reduce the total number of cases and deaths, as well as reduce peak demands on the healthcare system (data in Appendix Table S3) Depending on the threshold (ICU bed occupancy) at which lockdown periods were triggered, there was a tradeoff between having fewer, longer lockdown periods (lower threshold) and having more, shorter lockdown periods (higher threshold), with the higher thresholds resulting in less time spent in lockdown overall, but higher peak demands on ICU bed capacity Lower thresholds also resulted in more individuals remaining
			Intensive Interventions + Lockdown with 1000 bed trigger (national-level) Lockdowns are periods of particularly strict restrictions on movement Lockdowns phased in when ICU bed capacity reached certain thresholds, which would be kept in place until ICU bed usage fell back below the same	- Total Cases: 4M (1.8M-12M) - Total Deaths: 51K (21K -170K) - Cases in Peak Week: 110K (79K-800K) - Deaths in Peak Week: 1.4K (850-11K) - Peak ICU beds required: 5K (3.2K-39K) - Peak non-ICU beds required: 9.4K (6.2K-73K)	

Reference	Jurisdiction	Purpose	Methods and Strength of Predictions	Triggers	Conclusion
		projections on estimated new cases over time, patients requiring inpatient and critical care (intensive care unit, ICU) treatment, and deaths. Timeline: Simulations ran to December 31, 2021.	trigger threshold, to then be brought in again as needed.	- Time to peak cases (weeks) 60 (8-96) - Proportion of time spent in lockdown (29-Jan 2020 to 31-Dec 2021: 0.73(0.27-0.9) - Total Infected: 11M (4.3M-33M)	susceptible at the end of the simulation period, potentially increasing the total duration for which recurrent lockdowns would need to be maintained.
			Intensive Interventions + Lockdown with 2000 bed trigger (national-level)	- Total Cases: 6.5M (3M-14M) - Total Deaths: 84K (34K-200K) - Cases in Peak Week: 190K (110K-1.1M) - Deaths in Peak Week: 2.3K (1.3K-15K) - Peak ICU beds required: 8.1K (4.8K-55K) - Peak non-ICU beds required: 16K (9K-100K) - Time to peak cases (weeks) 46 (8-71) - Proportion of time spent in lockdown (29-Jan 2020 to 31-Dec 2021: 0.61 (0.23-0.77) - Total Infected: 18M (6.9M -36M)	
			Intensive Interventions + Lockdown with 5000 bed trigger (national-level)	- Total Cases: 9.7M (5.2M-17M) - Total Deaths: 130K (60K-240K) - Cases in Peak Week: 330K (200K-1.5M) - Deaths in Peak Week: 3.7K (2.3K-20K) - Peak ICU beds required: 13K (8.4K-71K) - Peak non-ICU beds required: 26K (16K-130K) - Time to peak cases (weeks) 34 (8-63) - Proportion of time spent in lockdown (29-Jan 2020 to 31-Dec 2021: 0.35 (0.12-0.5) - Total Infected: 27M (12M-41M)	

Note: Data in tables extracted directly from articles

Table 4. Triggers from Grey Literature and Jurisdictional Reports

Reference	Jurisdiction	Indicators/ Thresholds*	Predicting Variable(s)/Associated outcomes (NOTE: Documents were inconsistent in describing whether their indicators/ thresholds were being used to predict potential outcomes [e.g., ICU cases] or whether the indicators/ thresholds were being used to describe actions to be taken [e.g., public health interventions being reinstated])
British Columbia (BC) Public Health/Government https://www2.gov.bc.ca/assets/gov/health/about-bc-s-health-care-system/office-of-the-provincial-health-officer/covid-19/bc_covid-19_go-forward_management_strategy_web.pdf	BC, Canada	• Hospitalization, ICU and ventilator utilization to be measured • Conservative thresholds for critical care utilization to be developed as trigger	• Review and action for increased public health interventions.
Ontario Public Health/Government https://nationalpost.com/opinion/opinion-we-are-infectious-disease-experts-its-time-to-lift-the-covid-19-lockdowns	Ontario, Canada	200 new community cases of infections per day This is based on an estimate of the ability of the system to accommodate the required contact tracing for every diagnosed case at the provincial level.	Reinstitution of lockdown measures; evaluated on a province-wide threshold
Ontario Public Health https://www.ontariohealth.ca/sites/ontariohealth/files/2020-05/A%20Measured%20Approach%20to%20Planning%20for%20Surgeries%20and%20Procedures%20During%20the%20COVID-19%20Pandemic.pdf	Ontario, Canada	Considerations for planning in the system: • Community has a manageable (assessed weekly) level of disease burden or has exhibited a sustained decline in the rate of COVID-19 cases over the past 14 days • Organization has a stable rate of COVID-19 cases • Organization/ region have a stable supply of PPE • Organization/ region have a stable supply of medications	Hospital surgical or procedural activity capacity

		• Organization/ region have an adequate capacity of inpatient and ICU beds • Organization/region have adequate capacity of health human resources • Organization has a plan for addressing pre-operative COVID-19 diagnostic testing • Organization has confirmed that post-acute care outside the hospital is available and can be coordinated in a timely manner • Organization/ region have a wait list management mechanism in place to support ethical prioritization Metrics to gauge COVID-19 pressures: • COVID-19 hospitalizations • # of long-term care home outbreaks • In-hospital outbreaks • Hospital testing capacity and turn-around time Metrics to gauge resource availability: • Ward bed and ICU occupancy • Acute ALC bed occupancy • Emergency Department 'Time to Inpatient Bed' • Drug supply • Regional PPE supply	
Germany Public Health/Government https://nationalpost.com/opinion/opinion-we-are-infectious-disease-experts-its-time-to-lift-the-covid-19-lockdowns	Germany	50 new cases per 100,000 population per week	Hospital capacity

Bavarian State Government https://www.tagesschau.de/inland/coronavirus-deutschland-grenzwert-101.html	Bavarian State, Germany	35 new cases per 100,000 population per week	Hospital capacity
Berlin Regional Government https://www.tagesschau.de/inland/coronavirus-deutschland-grenzwert-101.html	City of Berlin, Germany	30 new cases per 100,000 population per week	Hospital capacity
Daniel K. Inouye Asia-Pacific Center for Security Studies https://www.preventionweb.net/files/submissions/71420_20.securitynexuscovid19lockdowneasingandrestrictingcolorframeworkforlocalgovernmentr1.pdf	United States	Metrics to gauge risk level Local case count: • New cases elsewhere in state = Steady Risk; • New local cases = Guard Risk; • 3 days increased local cases = High Risk • 3 days increased local cases = Critical Risk Basic criteria to inform increase/lift of lockdowns: • Epidemiological information, coordination, communication • Medical treatment/surge capacity • Operational coordination/management mechanisms • Testing availability, sentinel surveillance using population sampling • Contact tracing, monitoring, control • PPE availability, procurement, distribution • Workforce to manage related social support services	Decreased Public health coping capacity • Communities' ability to appropriately act and react to local changes in day-to-day exposure, risk, and capacity

		Local/state epidemic control task forces to establish local/state-applicable guidelines for varying levels of action	
American College of Surgeons https://www.facs.org/-/media/files/covid19/local_resumption_of_elective_surgery_guidance.ashx	United States	COVID-19 awareness: • Decrease in measures of new COVID-19 incidence for at least 14 days (based on estimated 75th percentile of incubation period prior to developing symptoms is 7 days, and maximum estimated incubation period is approximately 14 days) Preparedness: • PPE stored inventory, reliable supply chain for at least 30 days of operations	Hospital capacity for elective surgery (e.g., beds, ICUs, ventilators), including capacity in expansion strategies [e.g., weekends]): • Available resources, including OR capacity and alternative sites of care - — in addition to ORs and peri-anesthesia units—critical care, emergency, diagnostic imaging, and laboratory services • Potential sites for resuming elective surgery (e.g., OR, ambulatory surgery centers, hospital outpatient departments) • Cleaning—in all areas—along the continuum of care should be addressed (e.g., clinic, preoperative, ORs, workrooms, path-frozen, recovery room, wards, ICUs, ventilators, scopes, etc.) • OR schedule adaptability to accommodate rapid influx of cases • Post-corona elective surgery surge will not overwhelm local facility throughout preoperative, intraoperative, postoperative, and post-acute care phases • Other areas that support perioperative services be ready to commence operations, including clinical laboratory, diagnostic imaging, and sterile processing. If not ready, may be feasible to consider engaging outside partners in providing temporary support (e.g., national lab services) • Facility capacity for usual levels of emergency care, trauma care, others • Engineering issues (e.g., reversing negative flow ORs for COVID-19 to positive flow ORs for surgery)

Pennsylvania Governor's Office https://www.governor.pa.gov/process-to-reopen-pennsylvania/	Pennsylvania, United States	• # of cases – fewer than 50 new confirmed cases per 100,000 population reported over the previous 14 days • An assessment is made by Pennsylvania Department of Health if target goal (for local area) is met and county and local governments work to enable communities to reopen and transition back to work		Necessary considerations for reopening: Health system capacity • Adequate supplies of PPE and other supplies needed to conduct diagnostic testing, care for COVID-19 patients, and support other normal health care functions Diagnostic testing capacity • Community based testing, POC testing (e.g., primary care), serology testing as it becomes commercially available Surveillance capacity: • Robust surveillance, case investigation, contact tracing, and isolation of positive cases or quarantine of close contacts
Asian Pacific Society for Digestive Endoscopy https://gut.bmj.com/content/gutjnl/69/6/991.full.pdf	Hong Kong, China	COVID-19 in community	PPE supply	Endoscopy service
		Exponential increase in new cases of COVID-19	Critical (reserve <7 days)	• Urgent endoscopy only • Semi-urgent endoscopy- withhold • Elective endoscopy-withhold
		Rapid increase in new cases of COVID-19	Very low (reserve <4 weeks)	• Urgent endoscopy only • Semi-urgent endoscopy-to be individualized • Elective endoscopy-withhold
		Down trend in new cases of COVID-19	Suboptimal (reserve 4–8 weeks)	• Urgent endoscopy-fully capacity • Semi- urgent endoscopy – full capacity • Elective endoscopy – resumed with 50% capacity

		No new cases of COVID-19 diagnosed for at least 2 weeks	Normal (12 weeks reserve)	• Urgent endoscopy-fully capacity • Semi- urgent endoscopy – full capacity • Elective endoscopy – full capacity
Leon Tribe, University of Ottawa https://mysite.science.uottawa.ca/rsmith43/COVIDproliferation.pdf	Canada	Confirmed case count reaches 1 per 10,000 within population		Threshold for action (i.e., Public/personal intervention/mitigation)
New Zealand Alert Levels https://covid19.govt.nz/assets/resources/tables/COVID-19-alert-levels-detailed.pdf	New Zealand	Triggers vary by alert level: Level 4: • community transmission occurring, widespread outbreaks and new clusters – strong restrictions to limit all people movement/contact to contain community transmission and outbreaks • stay at home, other than for essential movement/work; stay in immediate household bubble Level 3 • community transmission might occur, new clusters emerge but can be traced and controlled – restrictions on activities, including at workplace and socially, to address high risk of transmission • stay at home, other than for essential personal movement, going to work/school; stay in extended bubble, which can now include close family or caregivers. Level 2		Does not state

		• household transmission could occur and isolated cluster outbreaks – physical distancing and restrictions on gatherings to address sporadic cases or cluster • businesses open, but physical distancing requirements apply; gatherings limited Level 1: • isolated household transmission - keep out global pandemic; population prepared for increase in alert levels if necessary • be prepared, and be vigilant; border measures are in place; public health measures in place, but no physical distancing is needed	

* Triggers/Thresholds included in this table are taken from reports, news articles, commentaries etc and may not explicitly state whether the proposed trigger/threshold is in use or will be in use for ongoing monitoring.

Appendix

List of Abbreviations

AHS: Alberta Health Services

COVID-19: Coronavirus Disease-2019

SAG: Scientific Advisory Group

KRS: Knowledge Resource Services

SARS-CoV-2: Severe Acute Respiratory Syndrome Coronavirus 2

HCU: Healthcare Utilization

ICU: Intensive Care Unit

ODE: Ordinary Differential Equation

SEIR: Susceptible-Exposed-Infection-Recovered

NPI: Non-Pharmaceutical Intervention

JHU: John Hopkins University

Methods

Literature Search

A literature search was conducted by Rachel Zhao, a Knowledge Resources Services (KRS) within the Knowledge Management Department of Alberta Health Services. Search was conducted in OVID MEDLINE on May 20, 2020, and LitCovid, TRIP Database Pro, PubMed, WHO COVID-19 Database, Centers for Disease Control and prevention, EBSCO COVID-19 Information Portal, Cambridge Coronavirus Free Access Collection, Oxford CEBM COVID-19 Evidence Search, National Collaborating Centre for Methods and Tools, Google, and Google Scholar on May 21, 2020. Citation tracking was conducted in Google Scholar. A total of 41 studies were included within this review document based on the below inclusion criteria:

Inclusion Criteria	Exclusion Criteria
- SARS-CoV-2 (COVID-19) (or SARS/MERS) - Describes a model(s) of projections for COVID transmission and/or cases in the upcoming months/years OR describes potential indicators or thresholds used to signal changes in case counts and healthcare utilization - Model includes public health restrictions in at least one scenario - Any population (humans) - Guidelines - Article is peer-reviewed, is from a reputable source or has described methodology (includes letters, abstracts, reviews)	- No model, projections or thresholds described - Primary focus is on characteristics of positive cases for COVID-19 - Influenza, RSV, circulating coronavirus, or other contagious virus as the primary focus of the paper

Search Strategy

Research Question 1

Ovid MEDLINE(R) and Epub Ahead of Print, In-Process and Other Non-Indexed Citations, Daily and Versions(R) 1946 to May 19, 2020

#	Searches	Results
1	exp Coronavirus/ or exp Coronavirus Infections/ or coronaviru*.mp. or "corona virus*".mp. or ncov*.mp. or n-cov*.mp. or "novel cov".mp. or COVID-19.mp. or COVID19.mp. or COVID-2019.mp. or COVID2019.mp. or SARS-COV-2.mp. or SARSCOV-2.mp. or SARSCOV2.mp. or SARSCOV19.mp. or Sars-Cov-19.mp. or SarsCov-19.mp. or SARSCOV2019.mp. or Sars-Cov-2019.mp. or SarsCov-2019.mp. or "severe acute respiratory syndrome cov 2".mp. or "2019 ncov".mp. or "2019ncov".mp.	34217
2	SARS Virus/ or Severe Acute Respiratory Syndrome/	5939
3	Middle East Respiratory Syndrome Coronavirus/	1037
4	(Middle East Respiratory Syndrome Coronavirus or MERS).kf,tw.	4724
5	or/1-4	36595
6	exp models, theoretical/	1751784
7	model*.kf,tw.	2873297
8	6 or 7	3786740
9	(predict* or estimat* or project* or forecast*).kf,tw.	2774366
10	5 and 8 and 9	997
11	limit 10 to (english language and yr="2020 -Current")	383

LitCovid

The Epidemic Forecasting section was screened and relevant articles were selected.

TRIP Database Pro

model* AND (predict* or estimat* or project* or forecast*) AND (coronaviru* OR "corona virus" OR ncov* OR n-cov* OR COVID-19 OR COVID19 OR COVID-2019 OR COVID2019 OR SARS-COV-2 OR SARSCOV-2 OR SARSCOV2 OR SARSCOV19 OR SARS-COV-19 OR SARSCOV-19 OR SARSCOV2019 OR SARS-COV-2019 OR SARSCOV-2019 OR "severe acute respiratory syndrome cov 2" OR "severe acute respiratory syndrome coronavirus*" OR "2019 ncov" OR 2019ncov OR Hcov*) from:2020

PubMed

((predict*[Title/Abstract] OR estimat*[Title/Abstract] OR project*[Title/Abstract] OR forecast*[Title/Abstract]) AND ((models, theoretical[MeSH Terms]) OR (model*[Title/Abstract]))) AND (((wuhan[tw] AND (coronavirus[tw] OR corona virus[tw])) OR coronavirus*[ti] OR COVID*[tw] OR nCov[tw] OR 2019 ncov[tw] OR novel coronavirus[tw] OR novel corona virus[tw] OR covid-19[tw] OR SARS-COV-2[tw] OR Severe Acute Respiratory Syndrome Coronavirus 2[tw] OR coronavirus disease 2019[tw] OR corona virus disease 2019[tw] OR new coronavirus[tw] OR new corona virus[tw] OR new coronaviruses[all] OR novel coronaviruses[all] OR "Severe Acute Respiratory Syndrome Coronavirus 2"[nm] OR 2019 ncov[tw] OR nCov 2019[tw] OR SARS Coronavirus 2[all]) AND (2019/12[dp]:2020[dp]))

WHO COVID-19 Database

(tw:("model"))

Research Question 2

Ovid MEDLINE(R) and Epub Ahead of Print, In-Process and Other Non-Indexed Citations, Daily and Versions(R) 1946 to May 19, 2020

#	Searches	Results
1	exp Coronavirus/ or exp Coronavirus Infections/ or coronaviru*.mp. or "corona virus*".mp. or ncov*.mp. or n-cov*.mp. or "novel cov".mp. or COVID-19.mp. or COVID19.mp. or COVID-2019.mp. or COVID2019.mp. or SARS-COV-2.mp. or SARSCOV-2.mp. or SARSCOV2.mp. or SARSCOV19.mp. or Sars-Cov-19.mp. or SarsCov-19.mp. or SARSCOV2019.mp. or Sars-Cov-2019.mp. or SarsCov-2019.mp. or "severe acute respiratory syndrome cov 2".mp. or "2019 ncov".mp. or "2019ncov".mp.	34217
2	Basic Reproduction Number/	865
3	(R0 or reproduction number or reproduction rate or reproductive number or reproductive rate or Rt or effective reproduction number or positive).kf,tw.	1680249
4	2 or 3	1680437
5	1 and 4	4192
6	limit 5 to (english language and yr="2020 -Current")	1206
7	(trigger* or lockdown* or lock* down or shutdown* or shut down* or reopen* or re-open* or restriction* or indicator* or threshold*).kf,tw.	478375
8	6 and 7	77

LitCovid

The Epidemic Forecasting section was screened and relevant articles were selected.

TRIP Database Pro

(trigger* or lockdown* or lock* down or shutdown* or shut down* or reopen* or re-open* or restriction* or indicator* or threshold*) AND (R0 or reproduction number or reproduction rate or reproductive number or reproductive rate or Rt or effective reproduction number or positive) AND (coronaviru* OR "corona virus" OR ncov* OR n-cov* OR COVID-19 OR COVID19 OR COVID-2019 OR COVID2019 OR SARS-COV-2 OR SARSCOV-2 OR SARSCOV2 OR SARSCOV19 OR SARS-COV-19 OR SARSCOV-19 OR SARSCOV2019 OR SARS-COV-2019 OR SARSCOV-2019 OR "severe acute respiratory syndrome cov 2" OR "severe acute respiratory syndrome coronavirus*" OR "2019 ncov" OR 2019ncov OR Hcov*) from:2020

PubMed

((trigger*[Title/Abstract] OR lockdown*[Title/Abstract] OR lock* down[Title/Abstract] OR shutdown*[Title/Abstract] OR shut down*[Title/Abstract] OR reopen*[Title/Abstract] OR re-open*[Title/Abstract] OR restriction*[Title/Abstract] OR indicator*[Title/Abstract] OR threshold*[Title/Abstract]) AND (R0[Title/Abstract] OR reproduction number[Title/Abstract] OR reproduction rate[Title/Abstract] OR reproductive number[Title/Abstract] OR reproductive rate[Title/Abstract] OR Rt[Title/Abstract] OR effective reproduction number[Title/Abstract] OR positive[Title/Abstract])) AND (((wuhan[tw] AND (coronavirus[tw] OR corona virus[tw])) OR coronavirus*[ti] OR COVID*[tw] OR nCov[tw] OR 2019 ncov[tw] OR novel coronavirus[tw] OR novel corona virus[tw] OR covid-19[tw] OR SARS-COV-2[tw] OR Severe Acute Respiratory Syndrome Coronavirus 2[tw] OR coronavirus disease 2019[tw] OR corona virus disease 2019[tw] OR new coronavirus[tw] OR new corona virus[tw] OR new coronaviruses[all] OR novel coronaviruses[all] OR

"Severe Acute Respiratory Syndrome Coronavirus 2"[nm] OR 2019 ncov[tw] OR nCov 2019[tw] OR SARS Coronavirus 2[all]) AND (2019/12[dp]:2020[dp]))

WHO COVID-19 Database

(tw:("lockdown")) OR (tw:("reopen")) OR (tw:("re-open")) OR (tw:("trigger"))

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