Estimated surge in hospitalization and intensive care due to the novel coronavirus pandemic in the Greater Toronto Area, Canada: a mathematical modeling study with application at two local area hospitals

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DECLARATION OF COMPETING INTERESTS

The authors have no competing interests to declare.

Abstract

Background: A hospital-level pandemic response involves anticipating local surge in healthcare needs.

Methods: We developed a mechanistic transmission model to simulate a range of scenarios of COVID-19 spread in the Greater Toronto Area. We estimated healthcare needs against 2019 daily admissions using healthcare administrative data, and applied outputs to hospital-specific data on catchment, capacity, and baseline non-COVID admissions to estimate potential surge by day 90 at two hospitals (St. Michael's Hospital [SMH] and St. Joseph's Health Centre [SJHC]). We examined fast/large, default, and slow/small epidemics, wherein the default scenario (R_0 2.4) resembled the early trajectory in the GTA.

Results: Without further interventions, even a slow/small epidemic exceeded the city's daily ICU capacity for patients without COVID-19. In a pessimistic default scenario, for SMH and SJHC to remain below their non-ICU bed capacity, they would need to reduce non-COVID inpatient care by 70% and 58% respectively. SMH would need to create 86 new ICU beds, while SJHC would need to reduce its ICU beds for non-COVID care by 72%. Uncertainty in local epidemiological features was more influential than uncertainty in clinical severity. If physical distancing reduces contacts by 20%, maximizing the diagnostic capacity or syndromic diagnoses at the community-level could avoid a surge at each hospital.

Interpretation: As distribution of the city's surge varies across hospitals over time, efforts are needed to plan and redistribute ICU care to where demand is expected. Hospital-level surge is based on community-level transmission, with community-level strategies key to mitigating each hospital's surge.

Keywords: COVID-19, pandemic preparedness, mathematical model, transmission model

INTRODUCTION

The COVID-19 pandemic caused by the SARS-Cov2 virus has led to over 1,914,916 detected cases and 123,010 deaths by April 15, 2020 (1). By March 6, 2020, there was direct evidence of local onward transmission in Canada (2). Local transmission refers to acquisition within a geographical locale (in this case, within Canada) but without a direct link to a travel-acquired case. Early evidence from China suggests that among patients diagnosed with COVID-19, 13.8% develop severe disease and 6.1% develop critical illness (3). Thus, an important component of responding to local onward transmission is preparing for a surge in inpatient and intensive care needs for patients with COVID-19 (4-6).

In the Canada's healthcare system, national, provincial, and local public health agencies provide guidance surrounding pandemic preparedness in the clinical setting, with implementation conducted within each city's health-care facilities. Indeed, decentralized implementation and hospital-level decision-making has played a major role in the current outbreak (7). Hospital-level pandemic planning teams need to integrate information on their local bed capacity, baseline admissions, and anticipated surge to help prepare their respective hospitals, including workforce planning, within the city, regional, and provincial-level responses (5).

To support hospital-level pandemic planning in the Greater Toronto Area (GTA), we developed an epidemic model and used publicly available data and provincial administrative healthcare data to simulate the range of plausible epidemic trajectories and hospital care needs that may be anticipated for the GTA. We then applied outputs from the epidemic model to hospital-specific data to estimate the early trajectory and daily volume of inpatient and intensive care surge at two downtown, acute-care hospitals in the GTA.

METHODS

Study Setting

The GTA has a population of 6 million and includes five regions (8-11) with 40 acute care hospitals (12). By March 20, 2020 there were 266 diagnosed cases of COVID-19 in the GTA (13-18). St. Michael's Hospital (quaternary care) and St. Joseph's Health Centre (tertiary care) are part of Unity Health Toronto, a network of two acute care and one long-term continuing care facility. The Unity Health Toronto COVID-19 Incident Management Team was formed on January 27, 2020 and requested rapid modeling to estimate potential surge in health-care needs at each hospital.

Model design

We developed a deterministic, compartmental, mathematical model of SARS-Cov-2 person-to-person transmission, and simulated a closed population (no births or deaths) over a 300-day period. For the current analyses, we did not stratify the modeled population by age and thus, we assumed a homogenous population. **Figure 1** depicts the model structure, where the biological component follows a susceptible-exposed-infectious-recovered system, and the health-care component includes admissions through inpatient and intensive care units. The model was written in R scripting language (source code available at our GitHub Repository (19)) and is detailed in **Appendix 1**. A R shiny user-interface was created for the model (20).

Parameter values and their data sources are shown in **Table 1**. **Appendix 1** details the biological, epidemiological, and clinical severity parameters; internal validity checks (case fatality proportions and serial intervals); and epidemic constraints.

Hospital-specific estimates (**Appendix 1**)
We used Institute for Clinical Evaluative Sciences (ICES) estimates on the median number (and inter-quartile range, IQR) of hospital admissions and intensive care unit (ICU) admissions in the GTA and at each hospital from March 2019 to August 2019 (12). Unity Health Toronto Decision Support provided daily census of non-ICU inpatients and ICU inpatients as a median (IQR) calculated over 90 days using March to June from the years 2014 to 2019 inclusive.

Intervention parameters
We applied two interventions with assumptions surrounding their values: physical distancing to reduce contacts by 20% started 30 days into the outbreak; and the proportion of non-severe cases who self-isolate (default 10%). Intervention parameters were fixed for the primary analyses, and varied in sensitivity analyses (0 to 70% reduction in contact rate; delay initiating physical distancing from 2 to 90 days after start of outbreak; increasing the proportion with non-severe infection who self-isolate [following testing or syndromic diagnosis] from 10% to a the maximum proportion of individuals with COVID-19 who may develop symptoms (41-69% (21-23)).

Epidemic constraints

To generate a plausible range of epidemic trajectories under best and worst-case scenarios, we sampled parameters as per **Table 1** while fixing the intervention parameters, and used the following constraints: the upper and lower bound of the per-capita, cumulative cases detected per day in Lombardy, Italy (24), and Hong Kong, China (25), respectively, within the first 30 days after detection of 3 cases. We then selected a slow/small epidemic and a fast/large epidemic using the lower and upper interquartile range in the peak incidence across the full, constrained set of epidemic trajectories. We defined a default scenario using the median or best-justified parameter values which passed our internal validity checks and epidemic constraints. We also examined the face validity of our default epidemic by comparing it to our synthesis the observed data in the GTA ((13-18, 26), **Appendix** 1).

Analyses

First, we reported epidemic features and health care needs estimated by the range of plausible scenarios and the three selected scenarios for the GTA. Second, we applied GTA model outputs from the three scenarios to generate hospital-specific estimates using the catchment proportion for non-ICU and ICU hospital admissions and added the baseline daily (median) number of inpatients on all non-ICU and ICU units for each hospital. We then compared the potential trajectories, under the assumption that baseline admissions remain the same, with the maximum capacity for non-ICU and ICU beds at each hospital. Third, we performed a one-way sensitivity analysis using the default scenario to identify the main sources of uncertainty when estimating hospital surge.

Ethics approval

This study was exempt from research ethics approval as the aggregate data provided by Unity Health Toronto Decision Support was not used to systematically investigate a hypothesis and thus, it was not considered human research as defined in TCPS2.

RESULTS

Figure 2 depicts the per-capita cumulative rate of confirmed cases across the plausible range of epidemics in the first 60 days of the outbreak, in the absence of further intervention. The default scenario follows a similar early trajectory of rapid growth in observed cases in the GTA, while the fast/large and slow/small epidemics are closer to, but not at the level of, Lombardy and Hong Kong, respectively (**Figure 2**).

Parameter values for the three scenarios are compared in **Appendix Table 2.1**. The slow/small epidemic had a smaller R_0: 1.84 vs. 2.4 in the default scenario. Transmission-related parameters were similar in the fast/large and default scenarios, except for a slightly higher proportion of the population already infected with COVID-19 at the start of the outbreak (initial seeding, 0.004% vs. 0.003% in the default scenario). However, cumulative confirmed cases (**Figure 2**, **Appendix 2 Figure 2.1**) were much lower in the

default scenario because of the clinical parameters: the proportion of individuals with COVID-19 with severe disease requiring hospitalization, and thus, detected, was 10.4% in the fast/large vs. 5.5% in the default scenario.

Comparing scenarios for hospital surge within the GTA

Figure 3a shows the epidemic curves in the absence of further interventions. Given the similar transmission parameters, the default and fast/large epidemic follow similar underlying patterns. As such, the default scenario represents a pessimistic scenario with 71.0% of the population infected by day 300.

In 2019, an estimated 1,056 to 1,653, and 145 to 231 patients were admitted each day to a non-ICU bed (**Figure 3b**) and to an ICU bed (**Figure 3c**) respectively. Despite similar underlying epidemics, the fast/large and default epidemics project different health-care needs driven by differences in probability of severe disease. In the absence of further interventions, ICU admissions in the small/slow epidemic still surpass the daily number of ICU admissions in 2019 (**Figure 3c**).

Appendix 2 Table 2.2 summarizes the peak number of admissions, and peak in daily census (prevalence) of inpatients within the first 300 days of the outbreak. Across all plausible scenarios, the IQR of peak prevalence in number of non-ICU inpatients with COVID-19 ranges between 10,189 and 38,502; and for ICU inpatients ranges between 2,454 and 17,651. In the default scenario, the model estimates a peak of 32,368 non-ICU and 7,418 ICU inpatient beds needed to care for patients with COVID-19 in the GTA.

Hospital-specific surge

Between March to August 2019, St. Michael's Hospital and St. Joseph's Hospital, respectively, received 4.5% (95% CI 4.4, 4.6) and 3.9% (95% CI 3.8, 4.0) of all non-ICU hospital admissions in the GTA; and 8.7% (95% CI 8.4, 9.0) and 2.3% (95% CI 2.1-2.5) of ICU admissions in the GTA. In the years from 2014-2019, the median daily non-ICU and ICU inpatient census at St. Michael's Hospital was 370-419 and 50-59, with a maximum capacity of 405 and 71 beds, respectively (**Appendix 1**). At St. Joseph's Health Centre, the median daily non-ICU and ICU inpatient census was 353-390 and 17-23, with a maximum capacity of 407 and 32 beds, respectively (**Appendix 1**).

Thus, the total daily census of non-ICU and ICU inpatients, with or without COVID-19 is shown in **Figure 4 and Figure 5** respectively for St. Michael's Hospital, and in **Appendix 2** for St. Joseph's Health Centre (**Figure 2.2 and 2.3**). The model estimates that if nothing changes with the baseline (pre-outbreak) levels of admissions, both hospitals will surpass non-ICU and ICU capacity under the fast/large and default scenarios within 90 days of the outbreak, but (as expected based on **Figure 3c**) that may not be the case with the small/slow epidemic (**Figures 4-5, and Appendix 2 Figure 2.2-2.3**). Driven by differences in their catchment, St. Michael's Hospital may expect an earlier surge around day 40 and St. Joseph's Health Centre, a later surge around day 65.

Table 2 provides the daily census (prevalence) of inpatients with COVID-19 from each scenario, the median and IQR of the full range of constrained model outputs for the

catchment of each hospital, and the relative reduction in non-COVID admissions or absolute increase in ICU beds needed to address the surge at each site. In the default scenario, for St. Michael's Hospital to remain below its non-ICU bed capacity 90 days into the outbreaks, the hospital would need to reduce non-ICU inpatient care for non-COVID by 70%, to open up 279 non-ICU inpatient beds; St. Michael's Hospital would also need to create 86 new ICU-beds in addition to its current capacity of 71 beds to be able to care for non-COVID and new COVID-related ICU inpatients (**Table 2**). At St. Joseph's Health Centre, under the default scenario, non-ICU beds and ICU-beds for non-COVID would need to be reduced by 58% and 72%, respectively, to open up 217 non-ICU beds and 13 ICU beds by 90 days into the outbreak, to remain below the hospital's respective bed capacity (**Table 2**).

Sensitivity analyses

Results of one-way sensitivity analyses using the default scenario, for non-ICU and ICU care are shown for St. Michael's Hospital in **Figure 6** and **Appendix 2 Figures 2.4-2.7**, respectively. Results of sensitivity analyses were similar for St. Joseph's Health Centre. At the hospital-level, uncertainty in local epidemiological features was more influential than uncertainty in clinical severity. For example, uncertainty in local seeding **(Figure 6a)** has a larger influence on non-ICU care at St. Michael's Hospital than uncertainty in clinical severity (**Figure 6b**). The effect of early versus delayed initiation of physical distancing has a large impact as shown in **Figure 6c**. If physical distancing could only reduce contact rates by 20%, then maximizing the diagnostic capacity or syndromic diagnosis at the community-level in the GTA could reduce the surge at St. Michael's hospital from 285 to 40 non-ICU patients with COVID-19 and 101 to 10 ICU patients with COVID-19 by day 90 of the outbreak.

DISCUSSION

In the absence of further interventions, even a best-case scenario like the simulated small/slow epidemic, may lead to a surge in ICU care in the city. However, the impact of the city's outbreak is expected to vary across hospitals by their local catchment, with local epidemic features driving each hospital's surge. The local transmission dynamics, or what was happening with the epidemic overall in the city, had a larger influence on a hospital's surge than uncertainty around disease severity. As such, community-level interventions, like maximizing diagnosis (via testing, or via syndromic case finding) among symptomatic individuals in the community could potentially mitigate the surge in each hospital.

Our estimates of the surge at the hospital-level align with the relative magnitude of surge at a macro-level as estimated from other modeling studies (provincial and national (27) in Canada, and in other settings (28)), but add to the literature by demonstrating potential variability with even minimal variability in hospital-context. The preliminary hospital-specific findings (on March 4, 2020) were used to prepare for the local surge at the two hospitals. First, the hospitals opened up beds by temporarily cancelling non-essential surgeries and procedures. Second, as most COVID-related inpatient care would fall under the hospitalist and medicine services, the relevant departments rapidly set up a separate

service with a viable back-up system and ability for rapid scale up in anticipation of increasing cases requiring admission, and staffing short-falls due to infection, exposure, or while awaiting test results if symptomatic. Third, ambulatory clinics were reduced with a focus on virtual care and urgent assessments only; this allowed clinic space to be consolidated to preserve personal protective equipment and human resources (including physicians) for deployment to other areas. This consolidation also allowed identification of potential inpatient spaces. There was also a change in health-care use by the public: non-COVID medicine admissions are dropping across the city and country (29). Thus, the next iteration of analyses will need to account for active and passive reductions in admissions.

Limitations include our assumption that the distribution of hospitalizations and ICU admissions would follow 2019 patterns, and that transmission was homogenous across the city. However, distribution of admissions may be expected to follow even more granular patterns of transmission in the hospital's neighborhood-level catchment area (30). Future work includes capturing heterogeneity within the five health units and near real-time adjustment of the catchment using observed patterns of hospital-specific admissions. Finally, our objective was to conduct a scenario-based analyses, and not to explicitly fit the model to observed cases, hospitalizations, ICU admissions and deaths in the GTA; these are the next step in supporting local GTA hospitals and re-distribution of ICU care across the city (31).

In summary, a surge in hospital capacity in the GTA is expected across a range of pessimistic to optimistic scenarios during the COVID-19 pandemic, with important and practical variability anticipated at the hospital-level. What is happening outside the hospital will have the largest influence on each hospital's surge, with an opportunity for increasing diagnostic (testing or syndromic) capacity to mitigate each hospital's surge, especially if there are pragmatic constraints on physical distancing measures. ICU admissions at the city-level is expected to surge past baseline even in best-case scenarios, but with variability across hospitals – thus, signaling the importance of efforts to plan and redistribute ICU care with where variability in surge may be expected.

DATA SHARING

Model codes and data are available at: https://github.com/mishra-lab/covid-GTA-surge-planning.

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Table 1. Transmission model parameters

	Units	Default value	Range examined in sensitivity analyses (uniform distribution)	Reference and Notes
Epidemiological				
Population size of Greater Toronto Area	Number	6,196,731	N/A	Projected estimate from 2016 census (1, 2) and a 1% annual change as per the United Nations Urbanization Prospects (3), and using the Census Metropolitan Area of Toronto (4).
R_0	Number	2.4	1.4-3.0	Range of estimates from modeling studies of outbreaks within and outside China, and on the diamond princess cruise ship (5-9). The lower bound was based on the lower bound estimate of R_0 from the WHO report of outbreaks in China (10). Systematic review and meta-analysis of studies of R_0 suggest that R_0 estimates have stablied in the range of 2-3 in more recent studies (11). Our default estimate of 2.4 was consistent with the assumption used in other modeling studies (12).
Incubation period	Days	5.2	3-9	Pooled analysis of 181 confirmed cases with identifiable exposure and symptom onset estimated an median incubation of 5.2 days.(13) We further extracted point (mean or median) estimates of incubation period from a list identified of studies in China and Singapore to inform the range estimates (5, 14-23)
Duration of latent infection	Days	2	1-3	Assumption based on the relatively short incubation period (5.2 days) and serial interval (4.4 days) of COVID-19; other models have used latent period of 3 days (24)
Duration of subclinical infectiousness	Days	3	2-6	Calculated based on the incubation period and the assumption on the duration of latent infection.
Duration of symptomatic infectiousness	Days	7	5-10	Based on duration of upper respiratory tract viral shedding among individuals with symptoms (25)

Serial interval	Days	NA	3.1-7.5	(5, 23, 26, 27). No default estimate was used, as serial interval was not used as an input parameter; only the range estimates were used for internal parameter validation (detailed in the Methods section).
Initial seeding	% of total population	0.0032%	0.0011-0.0048%	Assumption
Clinical				
Proportion diagnosed with COVID-19 who required hospitalization	%	10	6-20	As of March 23rd, 10% of confirmed cases in Canada were hospitalized (28) Data on 55,924 confirmed cases in China suggested that 19.9% of confirmed cases were severe including 6.1% in critical conditions (19). We therefore assumed that a range of 6%-20% of detected cases would require hospitalization in GTA. Indeed, the Toronto Public Health has reported 18 (6.4%) hospitalized cases out of 280 confirmed cases of COVID-19 as of March 24th (29).
Proportion infected with COVID-19 who were diagnosed	%	NA	41-69	Proportion infected who were diagnosed was not directly used as an input parameter; but indirectly – to calculate the proportion infected who required hospitalization (detailed below). Analyses on data from China as well as on Japan citizens returning from the repatriation flights revealed that 31%-59% of infected cases may not be detected due to asymptomatic infections or mild symptoms (30-32). We therefore assumed a default estimate of 55% (midpoint of the range) for proportion of infected cases that were detected.
Proportion infected with COVID-19 who required hospitalization	%	5.5	2.4-14	We calculated the proportion of infected individuals who require hospitalization using the proportion of detected cases which require hospitalization, and multiply by the proportion of infected cases which may be detected.
Proportion hospitalized who require ICU care	%	33	30-52	As of March 25th, 33% of hospitalized cases in the Toronto Public Health Unit required ICU (29). Similarly, as of March 23rd, 40% of hospitalized cases in Canada required ICU care (28). Based on data of 55,924 confirmed cases in China, cases with critical conditions and thus may require ICU care comprise 30% of confirmed cases with severe or critical

				conditions (19). Of 1590 hospitalized patients across 575 hospitals in China, 254 were of severe conditions, of whom 52% required ICU care or invasive ventilation (15). We did not estimate proportion of ICU patients among all hospitalized patients in China as many patients were hospitalized for isolation purpose only rather than due to disease severity in the settings of China.
Duration of hospital stay	days	12	10-13	Among 1032 hospitalized patients who did not require ICU care acoss 552 hospitals in China, their median length of hospital stay at the end of study follow-up was 12 (IQR: 10-13) days (16). This estimate was consistent with the estimates on length of hospital stay among discharged COVID patients (regardless of ICU stay) in China and Europe (14, 16, 17, 33-35).(refs)
Duration of ICU stay	days	8	5-13	There is limited data on length of ICU stay prior to transfer to to the medicine ward for post-ICU recovery. Of 23 ICU patients in Wuhan, who have been discharged to the medicine ward from the ICU, their median length of stay in ICU was 8 (IQR: 5-13) days (36).
Case-fatality proportion among those in ICU care	%	38%	17-62	Of 1590 hospitalized patients across 575 hospitals in China, 131 patients required ICU care or invasive ventilation, of whom 50 (38%) died (15). We also extracted estimates from several studies in China and in Europe regarding the crude mortality among ICU patients which ranged from 17-62% (16, 19, 34, 35, 37-40).
Case-fatality proportion among those diagnosed	%	NA	0.8-4.24	No default estimate was used, as case-fatality proportion among diagnosed was not used as an input parameter; only the range estimates were used for internal parameter validation (detailed in the Methods section). Our estimates of the case-fatality proportion among those diagnosed were informed by a range of evidence as shown below, taken into consideration of the uncertainty and heterogeneity in the estimates by geographic location and age:

				As of March 23rd, 2091 cases were reported in Canada with 23 death, indicating a crude case fatality of 1.1% (28). Using crude age-specific case-fatality among all confirmed cases in China (41), and adjusted for the age distribution of confirmed cases in Canada as of March 23rd (28), we obtained an overall crude case fatality of 2.5% in Canada. Estimates of case-fatality rate amomg confirmed cases after adjusting for time-lag to death ranged from 0.8% in China excluding Hubei province, 3.48% in China overall, and 4.24% in other countries and regions (42). Analyses using data of cases on Diamond Prince ship estimated an infection fatality rate of 0.5% and case fatality rate of 1.1% after adjusting for time lag to death, and standardizing the age to approximate the age distribution among confirmed cases in China (43).

Abbreviations: ICU: intensive care unit; NA: not applicable.

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Table 2. Prevalent number of baseline* inpatients and inpatients with COVID-19 in non-ICU and ICU beds in two acute care hospitals in the GTA, 90 days after outbreak started.

	Among selected scenarios**			Across 153 constrained epidemics***		
	Fast/Large	Default	Slow/Small	Median	Lower Quartile	Upper Quartile
SMH non-ICU inpatient beds (capacity=405; non-COVID-19 patients=399*)						
Daily prevalent number of non-ICU COVID-19 related inpatients	1757	285	7	73	12	402
Extra absolute number of non-ICU beds needed	1751	279	1	67	6	396
% of non-COVID-19 related non-ICU inpatients to be reduced	NA	70	0.3	17	2	99
SMH ICU inpatient beds (capacity=71; non-COVID-19 patients=56*)						
Daily prevalent number of ICU COVID-19 related inpatients	911	101	9	42	7	263
Extra absolute number of ICU beds needed	896	86	0	27	0	248
% of non-COVID-19 related ICU inpatients to be reduced	NA	NA	0	48	0	NA
SJH non-ICU inpatient beds (capacity=407; non-COVID-19 patients=374*)						
Daily prevalent number of non-ICU COVID-19 related inpatients	1537	250	6	64	10	352
Extra absolute number of non-ICU beds needed	1504	217	0	31	0	319
% of non-COVID-19 related non-ICU inpatients to be reduced	NA	58	0	8	0	85
SJH ICU inpatient beds (capacity=32; non-COVID-19 patients=18*)						
Daily prevalent number of ICU COVID-19 related inpatients	241	27	2	11	2	70
Extra absolute number of ICU beds needed	227	13	0	0	0	56
% of non-COVID-19 related ICU inpatients to be reduced	NA	72	0	0	0	NA

*The baseline number of non-COVID-19 patients was estimated based on the median daily number of inpatients on May 30th between 2014-2019 in each hospital.
**The fast/large epidemic and slow/small epidemic were selected as the upper and lower quartiles of peak incidence, respectively, within the first 300 days. The default scenario used the default parameter set as shown in Table 1.
***Among 200 simulated epidemics, 153 met the constraints using the observed data for Lombardy, Italy and Hong Kong, China (corresponding data points at day 30 since outbreak started were used as upper and lower bounds, respectively to constrain the epidemics).
Abbreviations: ICU: intensive care unit; NA: not applicable when number of COVID-19 related patients exceeded the hospital capacity; SJH: St Joseph Hospital; SMH: St Michael's Hospital.

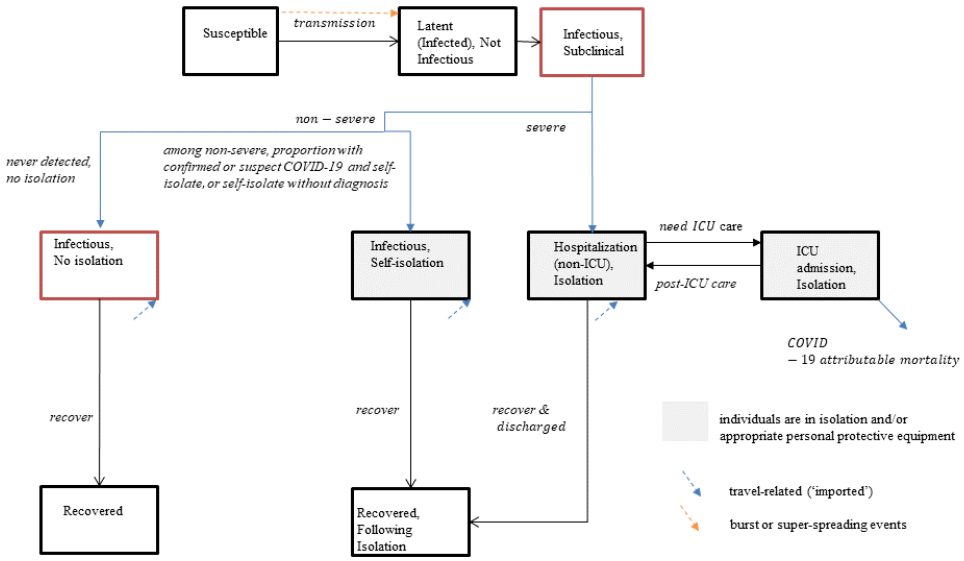


Figure 1. Transmission model structure. Compartments represent health-states, with transitions between health-states in a stable population of fixed size. A proportion of individuals infected with SARS-Cov-2 develop severe COVID-19 and require hospitalization. Among individuals with non-severe COVID-19, a proportion self-isolate after receiving a diagnosis of confirmed or syndromic COVID-19 or may self-isolate without a diagnosis; the remainder do not self-isolate. Only a subset of individuals with non-severe COVID-19 receive a confirmed diagnosis if they undergo testing. Individuals in the infectious health-states may pass the virus on to others. We assume that individuals in self-isolation or hospital-isolation cannot pass on the virus, but superspreading events are included to capture community, long-term care, and nosocomial (hospital-acquired) clusters of transmission events. Abbreviation: ICU: intensive care unit.

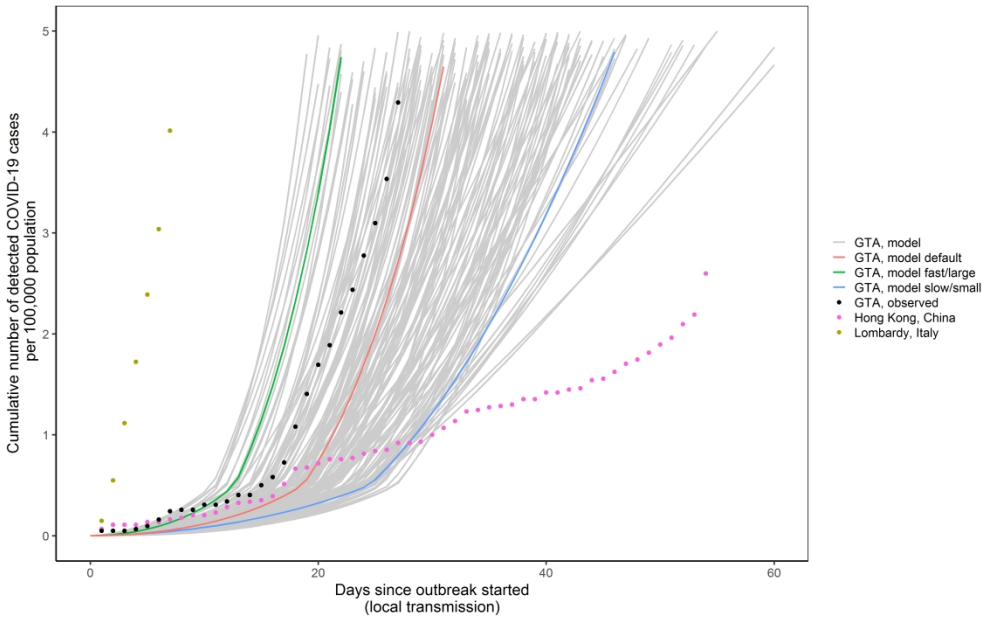


Figure 2. Cumulative detected cases per 100,000 population across simulated epidemic scenarios and observed data used for epidemic constraints. Model outputs from the sampled range of parameters in Table 1 which meet the model constraints are shown for detected cases as solid lines. The observed data for Lombardy, Italy and Hong Kong, China are shown as dotted lines, and the corresponding data points at day 30 since outbreak started were used as upper and lower bounds, respectively to constrain the epidemics. The observed data on cumulative detected cases for the Greater Toronto Area (travel-related, and local transmission) up to March 20, 2020 are also shown (dashed black line) as part of the face validity check. The model output for the fast/large epidemic is shown in green and slow/small epidemic in blue, selected as the upper and lower quartile of peak incidence, respectively, within the first 300 days. The default (solid red line) depicts the default scenario (Table 1). Simulated timeline begins at the start of the 'seeding' of the population with 0.0011-0.0048% of the population already infected with SARS-Cov-2. For observed data, we define outbreak started when 3 confirmed cases were observed. We chose 3 cases detected as the onset of epidemic based on the observed epidemic curve in the Greater Toronto Area, where the curve started to take off after detection of 3 cases. We applied the same threshold for other regions for comparability of epidemic curves across geographic locations. Abbreviations: GTA: Greater Toronto Area.

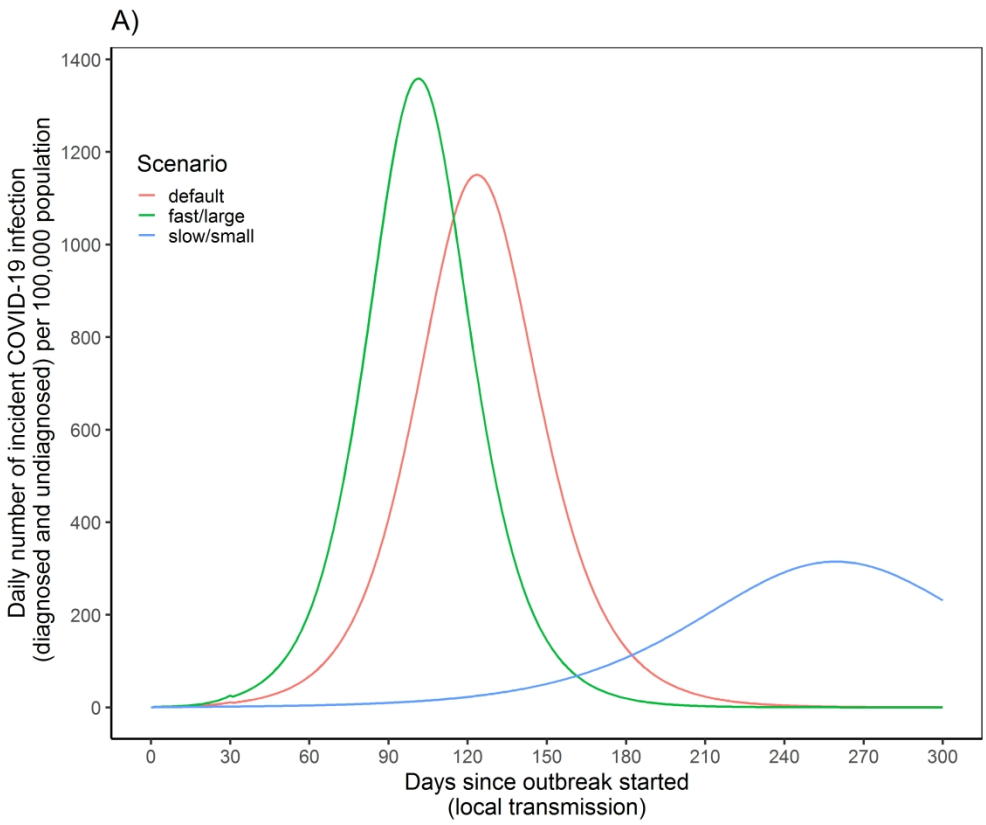


Figure 3(A). Incident epidemic curves and health-care needs in the Greater Toronto Area across three scenarios: default, fast/large, slow/small epidemics. (A) modeled incidence of infection (diagnosed and undiagnosed) for the GTA. The fast/large and slow/small epidemic scenarios are selected based on the upper and lower quartile of peak incidence, respectively, within the first 300 days across all simulated constrained epidemics; the default scenario reflects default parameter set in Table 1. All three scenarios (default, fast/large, and slow/small) assume that physical distancing started on day 30 and reduced contact rates by 20%, but has not increased nor decreased thereafter; and that the proportion of individuals with non-severe COVID-19 who self-isolate (e.g. via diagnosis of confirmed/suspected COVID-19) has not changed over the course of the epidemic. Abbreviations: GTA: Greater Toronto Area; ICU: intensive care unit.GTA: Greater Toronto Area; ICU: intensive care unit.

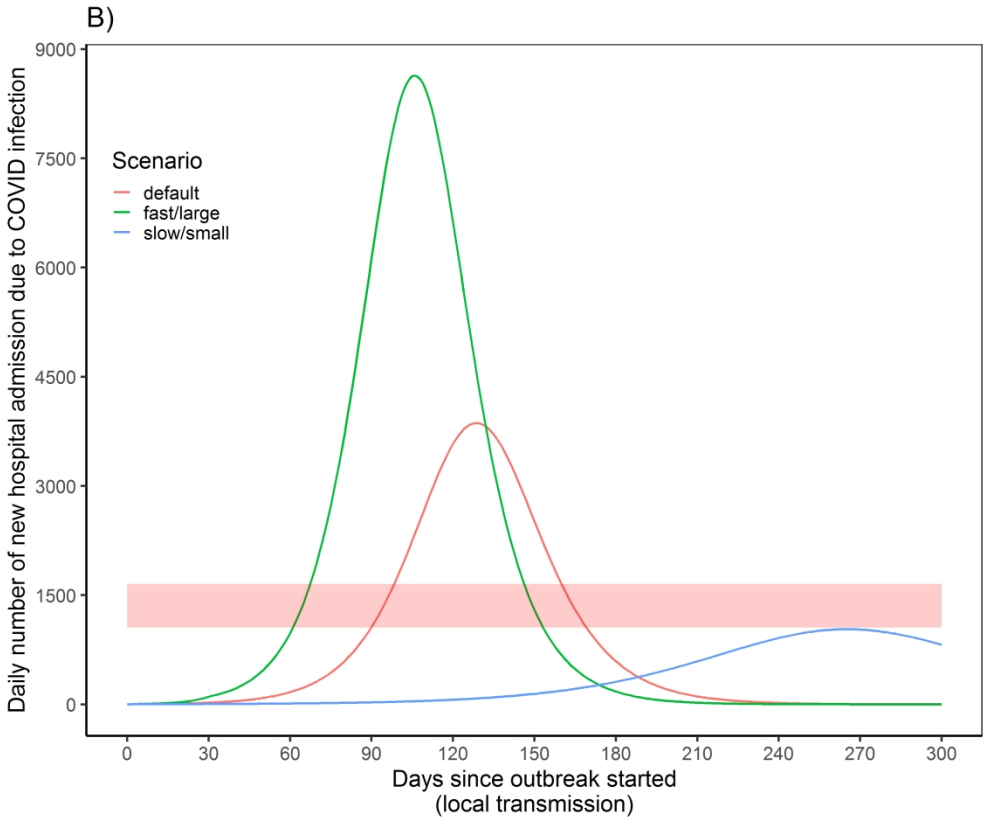


Figure 3(B). Incident epidemic curves and health-care needs in the Greater Toronto Area across three scenarios: default, fast/large, slow/small epidemics. (B) modeled daily number of hospital admissions for individuals with COVID-19 alongside pre-outbreak data on the daily median number of hospital admissions between March-August 2019 in the GTA. The fast/large and slow/small epidemic scenarios are selected based on the upper and lower quartile of peak incidence, respectively, within the first 300 days across all simulated constrained epidemics; the default scenario reflects default parameter set in Table 1. All three scenarios (default, fast/large, and slow/small) assume that physical distancing started on day 30 and reduced contact rates by 20%, but has not increased nor decreased thereafter; and that the proportion of individuals with non-severe COVID-19 who self-isolate (e.g. via diagnosis of confirmed/suspected COVID-19) has not changed over the course of the epidemic. Abbreviations: GTA: Greater Toronto Area; ICU: intensive care unit.Abbreviations: GTA: Greater Toronto Area; ICU: intensive care unit.

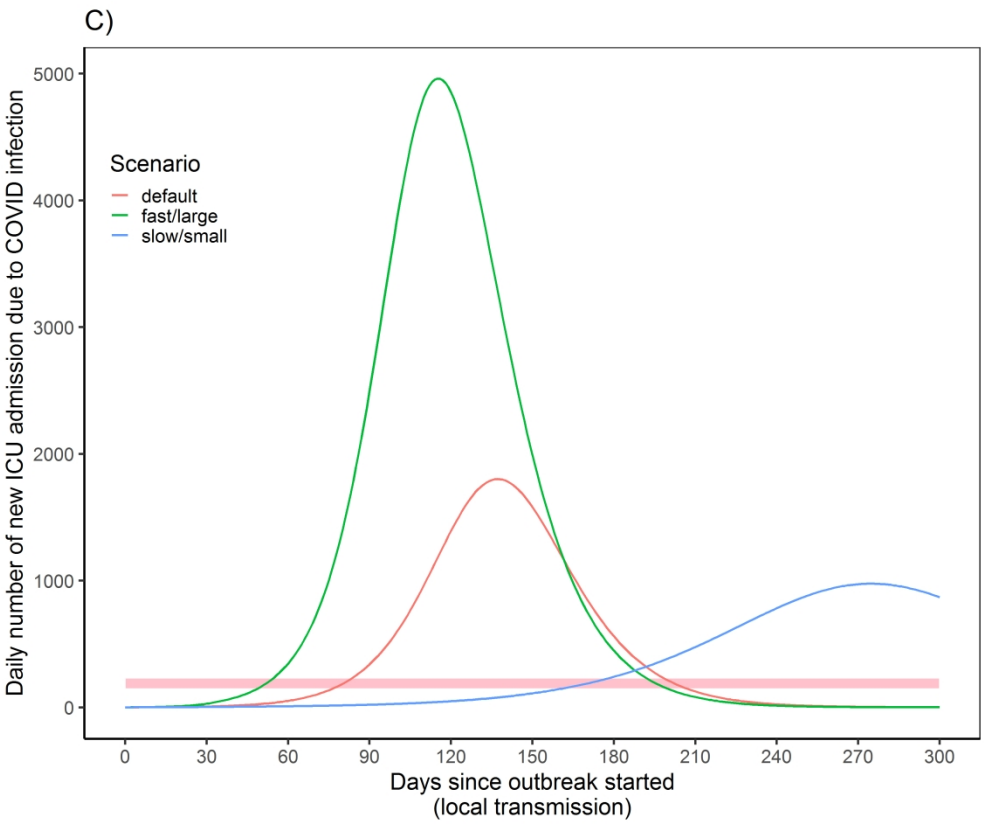


Figure 3(C). Incident epidemic curves and health-care needs in the Greater Toronto Area across three scenarios: default, fast/large, slow/small epidemics. (C) modeled daily number of ICU admissions alongside pre-outbreak data on the daily median number of ICU admissions between March-August 2019 in the GTA. The fast/large and slow/small epidemic scenarios are selected based on the upper and lower quartile of peak incidence, respectively, within the first 300 days across all simulated constrained epidemics; the default scenario reflects default parameter set in Table 1. All three scenarios (default, fast/large, and slow/small) assume that physical distancing started on day 30 and reduced contact rates by 20%, but has not increased nor decreased thereafter; and that the proportion of individuals with non-severe COVID-19 who self-isolate (e.g. via diagnosis of confirmed/suspected COVID-19) has not changed over the course of the epidemic. Abbreviations: GTA: Greater Toronto Area; ICU: intensive care unit.

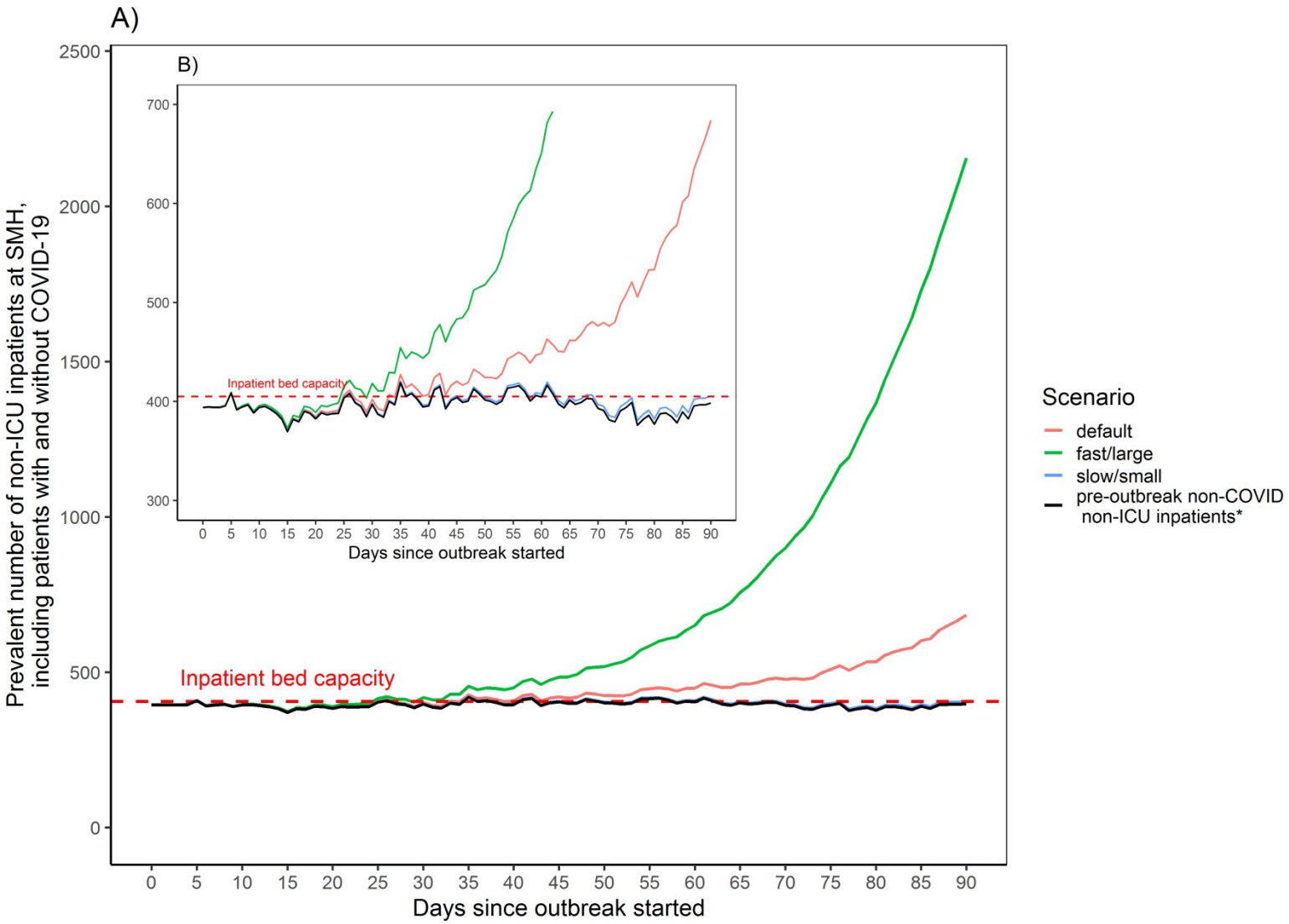


Figure 4. Estimated surge and capacity for non-ICU hospitalization at St. Michael's Hospital in the Greater Toronto Area. (A) Modeled number of non-ICU inpatients (including inpatients with and without COVID-19) and corresponding pre-outbreak baseline (non-COVID) number of non-ICU inpatients per day over 90 days. *Estimated by the median number of non-ICU inpatients at SMH between March – June, 2014-2019. (B) Same information as (A) but the y-axis ranged between 300-700. Estimates assume that distribution of non-ICU hospital admissions for patients with COVID-19 follows the pre-outbreak catchment of all non-ICU admissions across acute care hospitals in the GTA (March – August 2019), such that St. Michael's Hospital receives 4.5% of all non-ICU hospital admissions. Our use of observed data on hospital-specific non-ICU admissions during March-June (black line) are not meant to indicate a start-date of the outbreak as March 1. All three scenarios (default, fast/large, and slow/small) assume that physical distancing started on day 30 and reduced contact rates by 20%, but has not increased nor decreased; and that the proportion of individuals with non-severe COVID-19 who self-isolate (e.g. via diagnosis of confirmed/suspected COVID-19) has not changed over the course of the epidemic. Abbreviations: ICU: intensive care unit; SMH: St. Michael's Hospital.

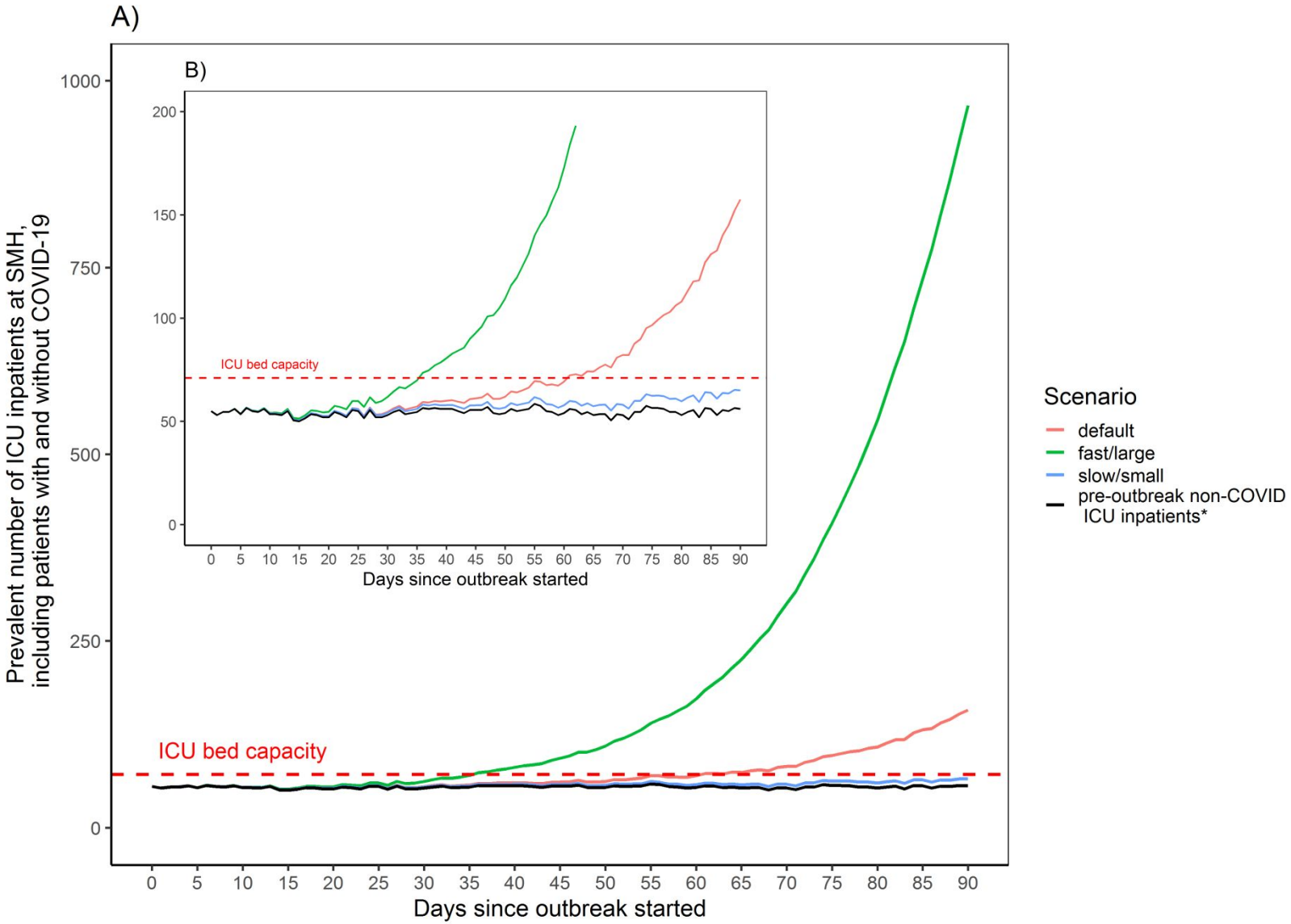


Figure 5. Estimated surge and capacity for ICU care at St. Michael's Hospital in the Greater Toronto Area. (A) Modeled number of ICU inpatients (including inpatients with and without COVID-19) and corresponding pre-outbreak baseline (non-COVID) number of ICU inpatients. *Estimated by the median number of ICU inpatients at SMH between March – June, 2014-2019). (B) Same information as (A) but the y-axis ranged between 300-700. Estimates assume that distribution ICU admissions for patients with COVID-19 follows the pre-outbreak catchment of all ICU admissions across acute care hospitals in the GTA (March – August 2019), such that St. Michael's Hospital receives 8.7% of all ICU hospital admissions. Our use of observed data on hospital-specific ICU admissions during March-June (black line) are not meant to indicate a start-date of the outbreak as March 1. All three scenarios (default, fast/large, and slow/small) assume that physical distancing started on day 30 and reduced contact rates by 20%, but has not increased nor decreased; and that the proportion of individuals with non-severe COVID-19 who self-isolate (e.g. via diagnosis of confirmed/suspected COVID-19 or without) has not changed over the course of the epidemic. Abbreviations: ICU: intensive care unit; SMH: St. Michael's Hospital.

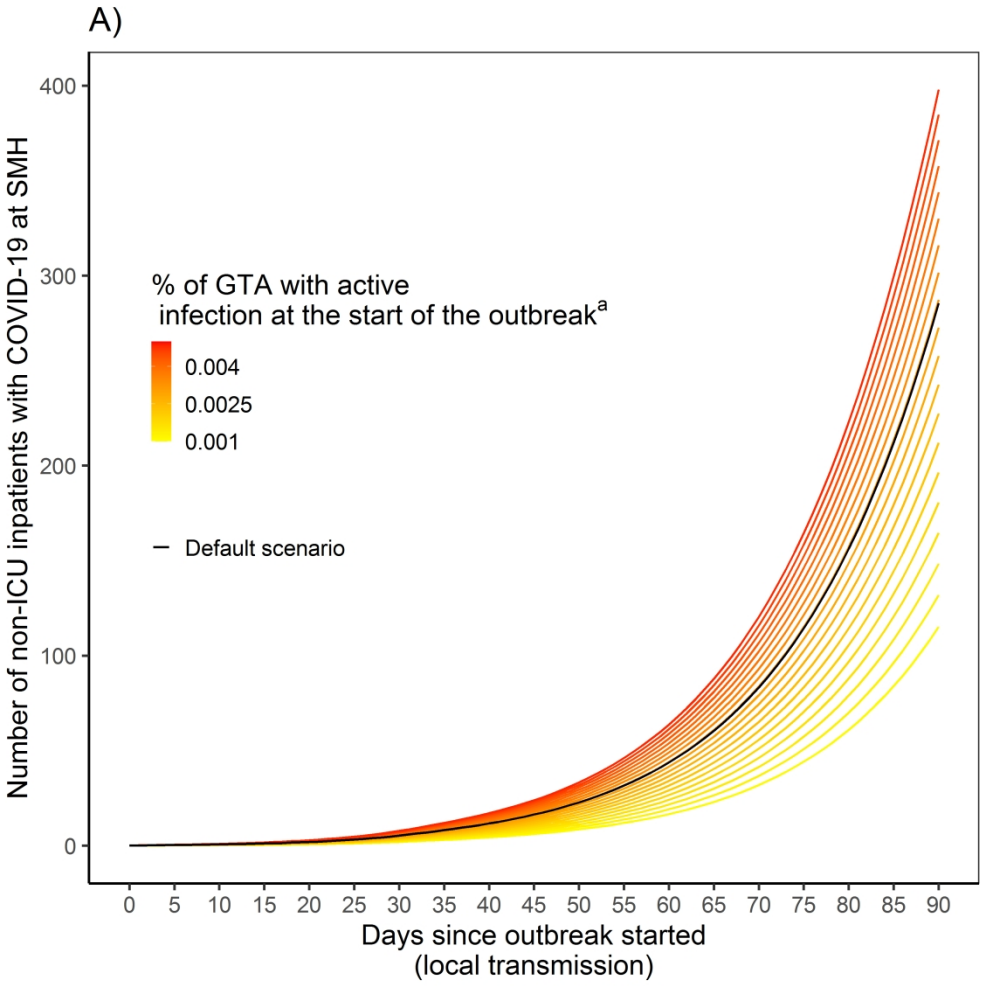


Figure 6(A). One-way sensitivity analyses using default epidemic scenario for prevalence of non-ICU inpatients with COVID-19 at St. Michael's Hospital. The influence of (A) seeding (proportion of population already infected with COVID-19 just at the start of the outbreak). Note that the y-axis scales for figures are different. Abbreviations: ICU: intensive care unit; SMH: St Michael's Hospital; GTA: Greater Toronto Area.

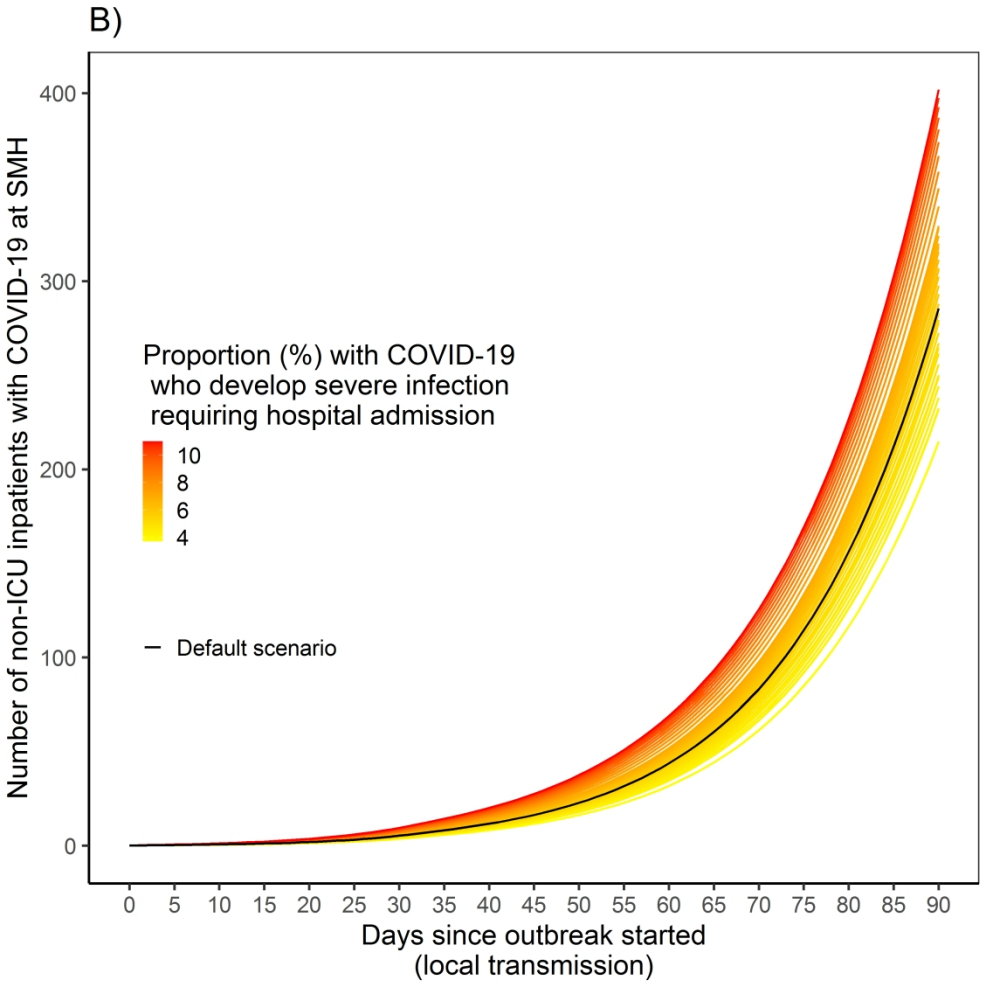


Figure 6(B). One-way sensitivity analyses using default epidemic scenario for prevalence of non-ICU inpatients with COVID-19 at St. Michael's Hospital. The influence of (B) clinical severity (proportion of individuals infected with COVID-19 who require hospitalization). Note that the y-axis scales for figures are different. Abbreviations: ICU: intensive care unit; SMH: St Michael's Hospital; GTA: Greater Toronto Area.

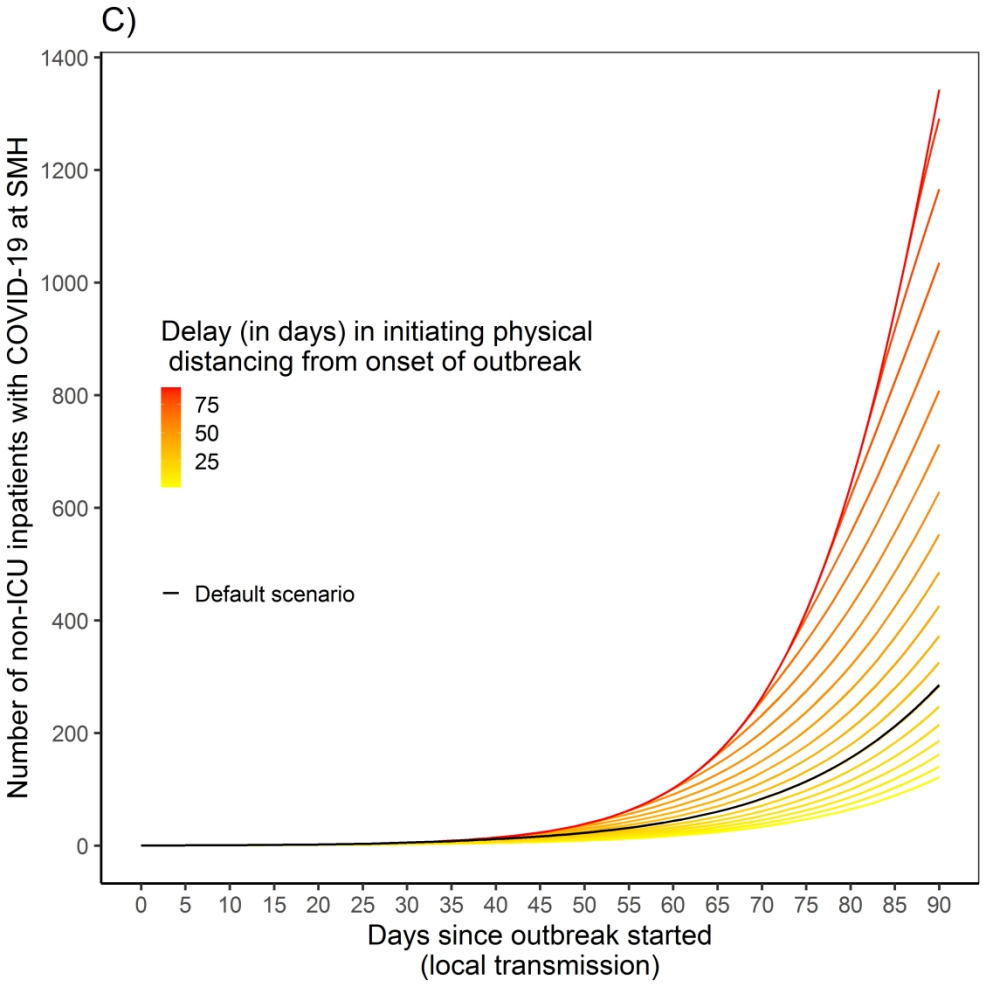


Figure 6(C). One-way sensitivity analyses using default epidemic scenario for prevalence of non-ICU inpatients with COVID-19 at St. Michael's Hospital. The influence of (C) earlier or later initiation of physical distancing (from start of outbreak to 60 days after outbreak started). Note that the y-axis scales for figures are different. Abbreviations: ICU: intensive care unit; SMH: St Michael's Hospital; GTA: Greater Toronto Area.

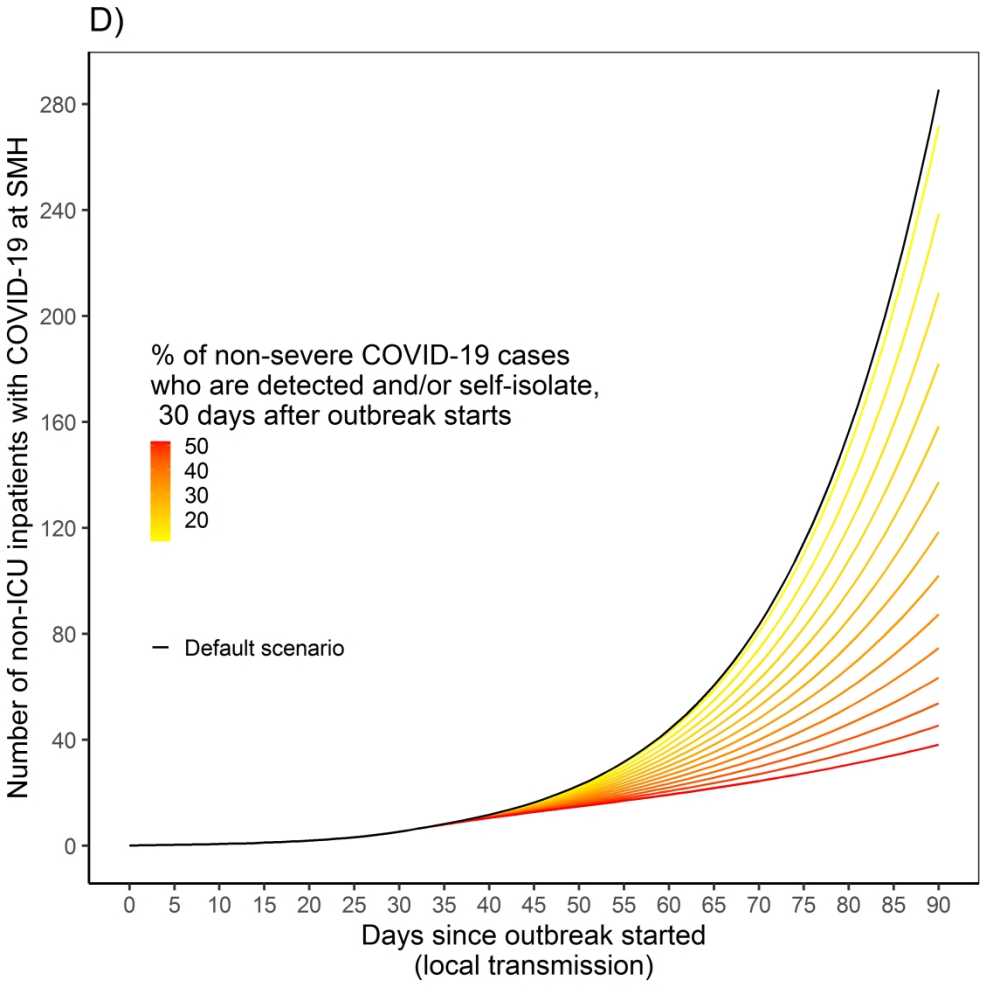


Figure 6(D). One-way sensitivity analyses using default epidemic scenario for prevalence of non-ICU inpatients with COVID-19 at St. Michael's Hospital. The influence of (D) proportion of individuals with non-severe COVID-19 who are diagnosed and/or self-isolate, 30 days after outbreak starts (e.g. due to increase capacity in testing in the community). Note that the y-axis scales for figures are different. Abbreviations: ICU: intensive care unit; SMH: St Michael's Hospital; GTA: Greater Toronto Area.

Appendix 1. Model Details & Parameterization

1.1 Overview

We developed a deterministic, compartmental mathematical model of SARS-Cov-2 virus transmission between person to person using a set of coupled differential equations. The state variables and their definitions are shown in **Table A1**, and the parameter definitions are shown in **Table A2**. The model simulates a closed population (no births, no baseline mortality). The model schematic with the state variables and transition parameters is shown in **Figure A1**. The model was written in R, and solved numerically using the deSolve package (1). The source code and all parameter files and outputs related to the study are available at our GitHub repository (2).

In the model, susceptible individuals acquired infection and entered a brief exposed or latent stage where they could not pass on the virus, followed by a subclinical but infectious stage (during which an individual may not experience symptoms), and then an infectious stage with or without symptoms. Following symptom onset, a subset of individuals developed severe disease and requires hospitalization; thus, we assumed that all individuals who develop severe disease are symptomatic. We assumed that among individuals with non-severe infection, a subset remained undetected and did not self-isolate when symptomatic; the rest self-isolated. The self-isolation compartment (I_{isol}) included individuals with a confirmed diagnosis based on polymerase chain reaction (PCR) testing, and suspect diagnosis based on symptoms and/or exposures (3, 4). Individuals within non-severe infections recovered and we assumed that all who recover had protective immunity during the time-period of analyses. Hospitalized individuals with COVID-19 could be detected as confirmed cases via testing. A proportion of individuals with severe infection required intensive care, among whom an COVID-19 attributable mortality rate was applied (5-13). Patients who recovered following inpatient and/or intensive care were discharged from the inpatient unit to the community.

The model included 'super-spreading' events as burst (one-time) events that occurred at a regular frequency to capture some dispersion around the average effective reproductive number and based on secondary attack rates from the literature and outbreaks in long-term care facilities or shelters (14, 15). Travel-acquired cases were included, of whom a subset with non-severe infection were diagnosed (confirmed or suspect) and isolated. We assumed that hospitalized patients were under isolation and did not contribute to the average contact rates at the population-level. We further assumed that hospitalized patients (and those who self-isolated) did not explicitly contribute to onward transmission. However, superspreading events may be interpreted as within-hospital (i.e. nosocomial), within long-term care or shelters, or via community transmission.

Table A1. State variables and their definitions.

Symbol	Definition
S	Susceptible
E	Exposed (latent stage), not infectious
I_{sc}	Infectious, subclinical
I_{ni}	Infectious, non-severe, not isolated (subclinical, symptomatic and not diagnosed)
I_{isol}	Infected, non-severe, self-isolation
I_{sev}	Infected, severe and hospitalized, isolation
I_{icu}	Infected, severe and admitted to intensive care unit (ICU)
R_{ni}	Recovered, never isolated and never diagnosed
R_{isol}	Recovered, had been in self-isolation and/or discharged from hospital

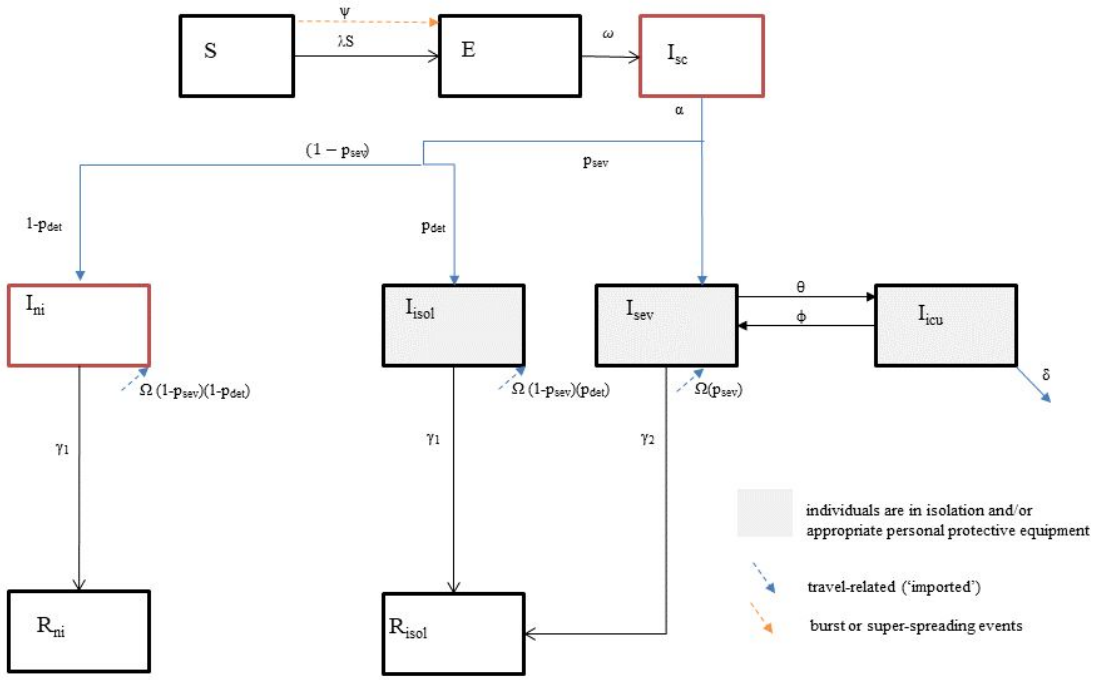


Figure A1. Transmission model schematic. State variables and parameters are defined in Table A1 and Table A2.

Table A2. Parameters and their definitions.

Symbol	Definition	Calculated
β	Probability of transmission (includes biological probability and contact rate)	$\beta = \frac{R_0}{duration\ infectiousness}$
λ	Force of infection per susceptible	$\lambda = \beta \frac{(I_{sc} + I_{ni})}{(S + E + I_{sc} + I_{ni} + R_{ni} + R_{isol})}$
ω	Per-capita rate of transition from E to I_{sc}	1/duration of latent (or exposed) period
Ω	Travel-related (imported) cases	See section 1.4 and (16) Travel-related cases (Ω) are imported via removal of a daily time-series of individuals from the S compartment to the various infectious, symptomatic compartments, based on the probability of severe infection, and probability of self-isolation/diagnosis among travel-related cases with non-severe infections. We assume that travel-related cases continue until the reproductive ratio (R_e) was less than 1.
ψ	Super-spreading or burst events	Super-spreading events (ψ) are included as burst or clustered transmission events by a recurring frequency of cases which continue until reproductive ratio (R_e) is less than 1. For the current analyses, we assumed 5 superspreading events every 11 days until the reproductive ratio was less than 1.
α	Per-capita rate of exit from I_{sc}	1/duration of subclinical period
p_{sev}	Probability of severe infection requiring admission	Among all infected
p_{det}	Probability of detection and isolation	Among individuals with non-severe infection, not travel-related
p_{det_tr}	Probability of detection and isolation	Among individuals with non-severe infection, travel-related
γ_1	Rate of recovery among individuals with non-severe infection	1/duration of symptomatic infection
γ_2	Rate of discharge to community, among patients hospitalized with severe infection	1/duration of hospitalization in non-ICU care
$condprob_{icu}$	Probability of ICU admission among patients admitted to hospital	See Table 1 in Main Text
θ	Rate of admission from non-ICU ward to ICU	$\theta = \frac{(-\ln(1 - condprob_{icu}) * \gamma_2)}{(1 + \ln(1 - condprob_{icu}))}$
φ	Rate of transition from ICU to non-ICU ward	1/duration of stay in ICU
$condprob_{cfr}$	Probability of death among patients with COVID, in the ICU	See Table 1 in Main Text
δ	Per-capita morality rate among patients with COVID in the ICU	$\delta = \frac{(-\ln(1 - condprob_{cfr}) * \varphi)}{(1 + \ln(1 - condprob_{cfr}))}$

1.2. Model equations

$$\frac{dS}{dt} = -\lambda S - \Omega - \psi \quad (1)$$

$$\frac{dE}{dt} = \lambda S + \psi - \omega E \quad (2)$$

$$\frac{dI_{sc}}{dt} = \omega E - \alpha I_{sc} \quad (3)$$

$$\frac{dI_{ni}}{dt} = \alpha I_{sc}(1-p_{sev})(1-p_{det}) + \Omega(1-p_{sev})(1-p_{det\_tr}) - \gamma_1 I_{sc} \quad (4)$$

$$\frac{dI_{isol}}{dt} = \alpha I_{sc}(1-p_{sev})(p_{\det}) + \Omega(1-p_{sev})(p_{det\_tr}) - \gamma_1 I_{isol} \quad (5)$$

$$\frac{dI_{sev}}{dt} = \alpha I_{sc}(p_{sev}) + \Omega(p_{sev}) + \varphi I_{icu} - \gamma_2 I_{sev} - \theta I_{sev} \quad (6)$$

$$\frac{dI_{icu}}{dt} = \theta I_{sev} - \varphi I_{icu} - \delta I_{icu} \quad (7)$$

$$\frac{dR_{ni}}{dt} = \gamma_1 I_{sc} \quad (8)$$

$$\frac{dR_{isol}}{dt} = \gamma_1 I_{isol} + \gamma_2 I_{sev} \quad (9)$$

1.3. Force of infection

We assume a homogenous population and consider that individuals who are isolated are no longer contributing to contact rates. As such, the probability of contact with an infectious individual uses the following denominator: sum of individuals in S, E, I_sc, Rnd, Rd. The consequence of such an assumption is that the impact of interventions such as increasing detection (and thus self-isolation) may be underestimated because individuals in the isolation compartment do not explicitly contribute to herd immunity (they do not 'consume' potential contacts).

1.4. Biological, clinical, and epidemiological parameters

Parameter values and their data sources are shown in **Main Text Table 1**. For the GTA transmission model, we sourced data for biological, epidemiological, and clinical severity parameters; internal validity checks; and epidemic constraints.

For biological and clinical parameters, we searched the peer-reviewed literature, pre-print literature, and publicly available reports from January 1, 2020 onwards. The literature search was not limited by country; however, at the time of our search on March 25, 2020, the majority of the published and preprint evidence was based on the outbreak in China, with a few data points from other countries including Singapore and Europe. We additionally searched the provincial- and city-level government official websites for COVID surveillance in Ontario and City of Toronto, and extracted relevant parameters of interest, wherever data is available. We used estimates of the key epidemiological parameter - the basic reproductive number (R_0) - from published and pre-print modeling studies of COVID-19 outbreaks within and outside China (17-24) to generate a plausible range of R_0 that could be applied to the GTA. We extracted estimates on disease incubation period (5-7, 17, 25-32), symptomatic

period (33), and serial intervals (17, 32, 34, 35) from pooled analysis as well as individual epidemiological and virological studies of COVID-19 to model the disease progression.

For parameters related to the probability of hospital admission and ICU admission, we used crude estimates the Public Health Agency of Canada reported on diagnosed COVID cases in Canada as of March 23rd as our default estimates (36). We extracted estimates on disease severity among confirmed and hospitalized cases in China (6, 7) to guide the range in probability of hospital admission and ICU admission, assuming all severe cases will require hospitalization and cases with critical conditions will require ICU care in the GTA context. We obtained estimates on the duration of hospital stay and ICU stay among hospitalized patients who were discharged without being admitted to ICU (5) and ICU patients who were discharged to the medicine ward (37), respectively, using data reported in China.

We extracted estimates on the case-fatality rate among ICU patients (5, 7-13) as well as among all confirmed cases in China (7, 11, 38) and in other countries or regions (39, 40). Wherever data is available, we sought for estimates adjusted for time-lag to death, and those stratified by age (details in **Main Text Table 1**).

1.4.2. Internal parameter validity checks on biological and clinical parameters

External estimates such as the overall case-fatality proportion among all diagnosed cases, and the serial interval were not directly used as input parameters in our model. However, they were correlated with other input parameters, and thus were used as interval validity checks to constrain our sampled parameter sets.

In the model, we assumed all deaths attributable to COVID are detected as confirmed cases and admitted to ICU prior to death. Therefore, we applied the following parameter in our model for COVID-19 attributable mortality: case-fatality proportion among patients in the ICU. As such, the overall case-fatality proportion among all diagnosed cases could be calculated using the product of the following parameters: probability of admission among diagnosed, probability of admission to ICU among hospitalized, case-fatality proportion among patients in ICU. We conducted internal validity checks to ensure the calculated case-fatality proportion among all diagnosed individuals fall within the external estimates of case-fatality among diagnosed cases obtained from the literature. The checks constrained the joint distribution of the above three parameters so that the overall case-fatality was consistent with observed data.

Similarly, we used estimates on duration of latent period, duration of sub-clinical period (calculated using the difference between incubation period and latent period), and duration of symptomatic period as our direct model parameter inputs to simulate disease progression. Given the definition of serial interval, we could calculate the minimum possible serial interval (*incubation period minus sub-clinical period*) and the maximum possible serial interval (*incubation period plus symptomatic period*) based on the above input parameters (41). We conducted internal validity checks to ensure the minimum calculated serial interval is lower than the upper bound of the external estimates on serial interval; and the maximum calculated serial interval is higher than the lower bound of the external estimates on serial interval. The checks constrained the joint distribution of the above parameters so that our modelled disease progression reflected epidemiological evidence on the serial intervals of COVID.

Modeled estimate of confirmed cases

To calculate the cumulative number of diagnosed cases in the simulated epidemics, we applied a probability of polymerase chain reaction (PCR) testing while admitted (I_{sev} and I_{icu}) and among those who self-isolate (I_{isol}); both values increased after the observed number of diagnosed cases in the GTA exceeded the expected number of travel-related, diagnosed cases 48 days after detection of the first confirmed case (Section 1.5).

The initial value for probability of PCR testing while admitted was 0.6 (tau_1), reflecting the practice of sentinel testing in the province and at the hospital-level prior to first diagnosed case of local transmission in the GTA. During the week of March 8, 2020, the provincial health laboratory had conducted 700 sentinel testing among inpatients with an acute respiratory illness whose health care providers had submitted a nasopharyngeal swab test for other respiratory viruses. Based on publicly available data from the Canadian Institute for Health Information data for 2017-2018, there are an average of 510 hospitalizations per week for pneumonia and 607 hospitalizations per week for chronic obstructive pulmonary disease or bronchitis. Assuming that pneumonia and chronic obstructive pulmonary disease or bronchitis are indications for nasopharyngeal swabs for respiratory virus testing, and all cases of severe COVID-19 could fit under these two diagnoses, then sentinel testing would have been conducted on 63% of hospitalized patients. At St. Michael's Hospital, sentinel testing (prior to first diagnosed case of local transmission) was conducted for 30 patients per week, and the daily census of hospitalized patients with an acute respiratory illness was 60-70 with a median length of stay of 7 days, leading to 65 new admissions per week, and as such sentinel testing would have captured 0.5. We then increased tau_2 to 0.9 to reflect nearly perfect testing of all hospitalized patients with symptoms compatible with COVID-19, after observed number of diagnosed cases in the GTA exceeded the expected number of travel-related, diagnosed cases.

The values for probability of testing among those who self-isolate was based on initial and revised testing criteria at assessment centers in the GTA, which varied considerably. At the time of analyses, we did not have access to data on testing nor positivity rates in the GTA. Thus, we used a probability of PCR testing of 0.1 and then 0.2 (tau_1) after observed number of diagnosed cases in the GTA exceeded the expected number of travel-related, diagnosed cases. The low probability of PCR testing reflected limitations on diagnostic capacity (test reagents and swabs) in the GTA, which meant PCR testing had to be prioritized to patients requiring hospitalizations and other higher-risk groups.

1.5. Travel-imported cases

To generate a daily number of diagnosed, imported cases (based on date of diagnosis) for the transmission model, we used surveillance data on travel-related cases diagnosed in the Greater Toronto Area (42) between Jan 25 and March 12, 2020. We then extrapolated the cumulative number of diagnosed, travel-related cases using a linear extrapolation in the Greater Toronto Area (**Figure A2**). We used the extrapolation of the cumulative number to generate a daily time-series, and used the daily time-series for the Greater Toronto Area in the transmission model (16). We assumed that the proportion with non-severe infection who have a travel history are more likely to be diagnosed or self-isolate (default p_{det_tr} =0.2, range 0.10-0.50).

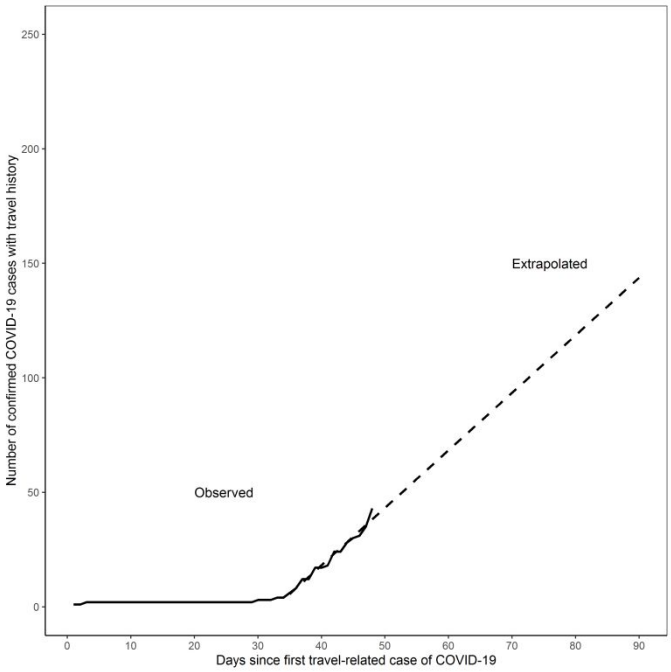
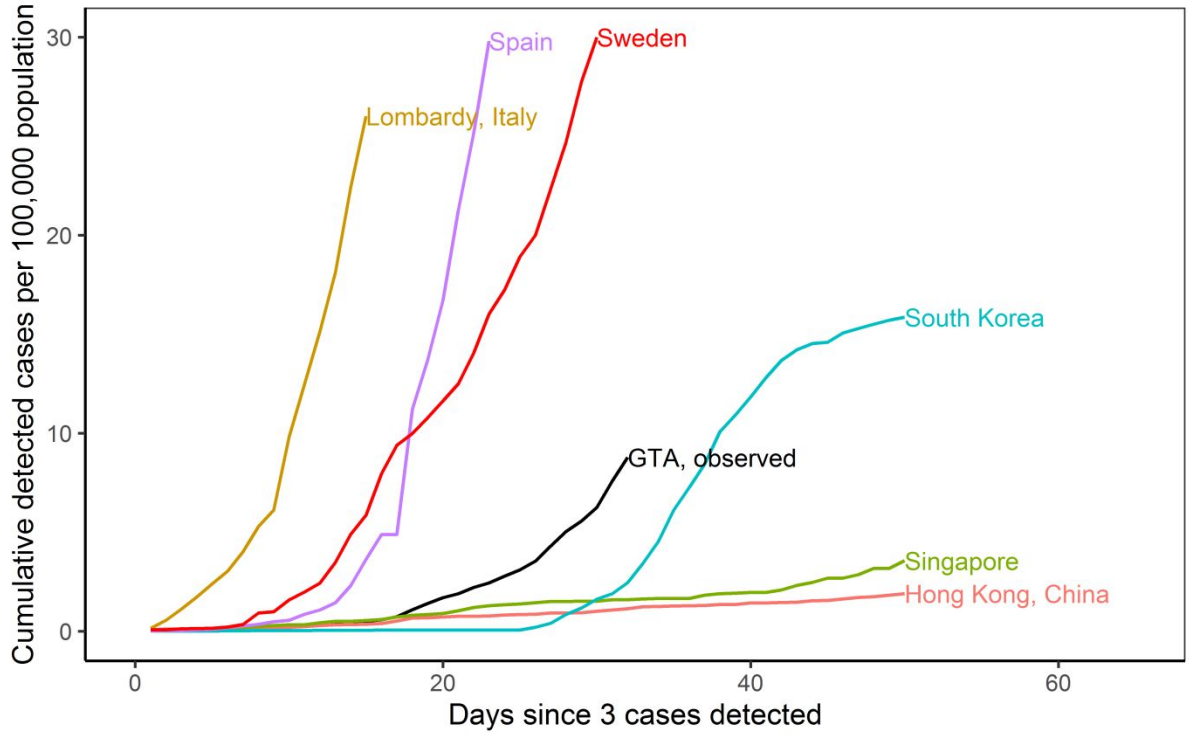


Figure A2. Observed and extrapolated number of travel-related COVID-19 cases in the Greater Toronto Area.

1.6. Data on epidemic curves for model constraints

1.7.1. Global confirmed cases by country and/or region

We obtained time series of daily cumulative confirmed cases in Spain, Sweden, South Korea, Singapore and Hong Kong, China from the open data sources provided by the John Hopkins dashboard (43, 44). We supplemented the open source data for Lombardy, Italy, using data provided from the Wikipedia page on the coronavirus pandemic in Italy (45). The epidemic trajectories in these settings are shown in **Figure A3**, reflecting a range of epidemic scenarios. We used the observed data 30 days after detection of at least 3 cases in Lombardy, Italy as the upper bound and in Hong Kong, China as the lower bound to constrain our model simulated epidemic scenarios.



[**Figure A3: Epidemic trajectories in the Greater Toronto Area and other settings.** We chose 3 cases detected as the onset of epidemic based on the observed epidemic curve in the Greater Toronto Area, where the curve started to take off after detection of 3 cases. We applied the same threshold for other settings for comparability of epidemic curves across geographic locations. The last date shown in this figure for each of the regions are as follow: Greater Toronto Area (March 25, 2020); Hong Kong, China (March 14, 2020); Lombardy, Italy (March 6, 2020); Singapore (March 13, 2020); South Korea (March 15, 2020); Spain (March 18, 2020); Sweden (March 26, 2020). Abbreviations: GTA: Greater Toronto Area.

1.7.2. Greater Toronto Area (GTA)

At the time of analyses, data on number of diagnosed cases in the GTA were not publicly available from a single source. GTA data are now publicly available from iPHIS but are provided based on accurate episode date. We had to constrain epidemics using the data as reported in other settiings (i.e. by date of detection) and thus we manually collated data from all publicly available sources and synthesized into a single time-series which we made publicly available on our GitHub repository (46).

The GTA consists of the City of Toronto, Durham region, Halton region, Peel region, and York region. The daily cumulative number of cases in the GTA was obtained through the summation of individual daily case data for Toronto and the four regions. As of March 25, the number of confirmed cases for Toronto and the four regions were updated on a daily basis using data reported by their respective city/regional governments. Historical data prior to March 25 was obtained through various means, depending on availability of data from the city/regional governments' websites. We used and presented data up to March 25 for the cumulative number of confirmed cases in GTA in the current study; the time series of GTA cases overall and by each region are available on the GitHub respository (46). We expect potential reporting delay of 2-3 days in our time series compared to the iPHIS data (the complete data with date of case detection is yet made publically available).

City of Toronto
Official press release from the City of Toronto was used as the primary source of data (47). Where this information was missing (due inconsistent frequency of reporting prior to March 17), one of the following methods was used to estimate the number of confirmed cases: referred to the data in the Public_COVID-19_Canada database created by the COVID-19 Canada Open Data Working Group (42) which recorded historical data from the Government of Ontario website (48); or imputed data given the known time lag in reporting between the provincial and regional governments as approximated from historical data from other regional governments.

Missing data from primary source:
March 6 and prior: using other regional datasets with consistent historical reporting of their daily cases (i.e., Durham region (49) and York region (50)) as a reference, it could be seen that data from the Public_COVID-19_Canada database is consistent with the reporting from the regional governments. Assuming the same for the City of Toronto, data from the Public_COVID-19_Canada database was used to fill in any missing information gap.

Between March 7 and 16: the missing data was imputed by using the observed time lag between other regional datasets and the Public_COVID-19_Canada database during this time period and using data from the Public_COVID-19_Canada database (42).

March 17 and onwards: data was obtained through daily press release by the City of Toronto (47) and if a single day of data was missing, the number of confirmed cases was approximated by using the median value of the number of cases reported the day prior and the day after.

Durham Region
Information posted on the Durham Region website was used as the primary source of data (49).

Halton Region
Information posted on the Halton Region website was used as the primary source of data (51). Where this information could not be obtained via the primary source (March 17-24), data was obtained through the Public_COVID-19_Canada database. Given the low number of cases reported by March 25 as well as a fairly slow increase in the number of cases, it was not necessary to impute the missing data using time lag.

Peel Region
Information posted on the Peel Region website was used as the primary source of data (52). Where this information could not be obtained via the primary source (March 9-24), data was obtained through the Public_COVID-19_Canada database. Given the low number of cases reported by March 25 as well as a fairly slow increase in the number of cases, it was not necessary to impute the missing data using time lag.

York Region
Information posted on the York Region website was used as the primary source of data (50).

Adjustments to the cumulative count for GTA
Data sources either report the daily number of new cases confirmed or the cumulative number of cases. If the daily number of cases was reported, the number was added to the previous day's cumulative number of cases. Some news sources did not distinguish between presumptive and confirmed cases. In those instances, a second source was used to verify the status of the case. Where this was not possible, it was assumed that the case was confirmed as infected by COVID-19.

A time lag between the data reported by the Government of Ontario (as seen through the Public_COVID-19_Canada database) and the data reported by the city/regional governments was observed starting from March 8. The time lag issue was first brought to attention by the discrepancy between provincial and regional numbers for total confirmed cases (53). This discrepancy in reporting numbers was suggested to be the result of reporting delay (54). Given this, the time lag observed was assumed to be a general reporting delay between all city/regional levels of government and the provincial government. Thus, data released by the Government of Ontario (and by extension, the Public_COVID-19_Canada database) was not used as the primary source of data; but it was used when the primary source of data was not available or for the purposes of data imputations.

1.5. Data on hospital and ICU admissions in the Greater Toronto Area

We used the following report provided by ICES to Unity Health Toronto Infection Prevention and Control and Pandemic Planning Committee (55). The following ICES data sources were used to generate estimates of hospital and ICU admission. We excluded: Admissions of non-Ontario residents; those missing patient age or sex; those aged 105 y or older; those who had a death date before the admission date.

1) Ontario Health Insurance Plan (OHIP) Registered Persons Database (RPDB): The RPDB provides basic demographic information (age, sex, location of residence, date of birth, and date of death for deceased individuals) for those issued an Ontario health insurance number. The RPDB also indicates the time periods for which an individual was eligible to receive publicly funded health insurance benefits and the best known postal code for each registrant on July 1st of each year.
2) Canadian Institute for Health Information (CIHI) Discharge Abstract Database (DAD): The DAD is compiled by CIHI and contains administrative, clinical (diagnoses and procedures/interventions), demographic, and administrative information for all admissions to acute care hospitals, rehab, chronic, and day surgery institutions in Ontario.
3) CIHI National Ambulatory Care Reporting System (NACRS): The NACRS is compiled by CIHI and contains administrative, clinical (diagnoses and procedures), demographic, and administrative information for all patient visits made to hospital- and community-based ambulatory care centres (emergency departments, day surgery units, hemodialysis units, and cancer care clinics).
4) CIHI Same Day Surgery Database (SDS): The SDS is compiled by CIHI and contains administrative, clinical (diagnoses and procedures), demographic, and administrative information for all patient visits made to day surgery institutions in Ontario. The main data elements include patient demographics, clinical data (diagnoses, procedures, physician), administrative data (institution/hospital number etc.), financial data, service-specific data elements for day surgery and emergency.
5) Ontario Healthcare Institution Information System (INST): The Institution Information System (INST) database contains information on health care institutions funded by the Ontario Ministry of Health. The database includes information on beds available in acute care hospitals and geographic information regarding hospital location.
6) Ontario Health Insurance Plan (OHIP) Claims History Database: The OHIP claims database contains information on inpatient and outpatient services provided to Ontario residents eligible for the province's publicly funded health insurance system by Ontario physicians. The main data elements include encoded patient and physician identifiers, fee codes for services provided, date of service, associated diagnoses, and the fees paid.

GTA residency was defined as census divisions (CD) in Toronto, Durham Region, Halton Region, Peel Region and York Region. Institutions in the GTA were defined using census subdivision (CSD) in Ajax, Clarington, Brock, Oshawa, Pickering Scugog, Uxbridge, Whitby, Burlington, Halton Hills, Milton, Oakville, Brampton, Caledon, Mississauga, Aurora, East Gwillimbury, Georgina, King, Markham, Newmarket, Richmond Hill, Vaughan, Whitchurch-Stouffville.

ICU admissions were defined using the DAD Special Care Unit variable coded as follows:
10 = Medical Intensive Care Nursing Unit
20 = Surgical Intensive Care Nursing Unit
25 = Trauma Intensive Care Nursing Unit
30 = Combined Medical/Surgical Intensive Care Nursing Unit

35 = Burn Intensive Care Nursing Unit
40 = Cardiac Intensive Care Nursing Unit Surgery
45 = Coronary Intensive Care Nursing Unit Medical
50 = Neonatal Intensive Care Nursing Unit Undifferentiated/General)
51 = Neonatal Intensive Care Nursing Unit Level 1
52 = Neonatal Intensive Care Nursing Unit Level 2
53 = Neonatal Intensive Care Nursing Unit Level 3
60 = Neurosurgery Intensive Care Nursing Unit
70 = Paediatric Intensive Care Nursing Unit
80 = Respirology Intensive Care Nursing Unit
90 = Step-Down Medical Unit
93 = Combined Medical/Surgical Step-Down Unit
95 = Step-Down Surgical Unit
98 = Provincially/Territorially Defined

The estimates from the report, including catchment area for the two hospitals are provided in **Table A3**.

Table A3. Descriptive statistics and proportions of acute care admissions and ICU admissions in the GTA by month in 2019.

		Total number of hospital admissions in GTA in calendar month	Number of patients admitted to hospital per day			Total number of ICU admissions in GTA in calendar month	Number of patients admitted to ICU per day		
Month	**Year**	**Total**	**Median**	**IQR_lower**	**IQR_upper**	**Total**	**Median**	**IQR_lower**	**IQR_upper**
March	2019	43,429	1,549	1,064	1,610	5,652	192	145	211
April	2019	43,233	1,602	1,056	1,643	5,936	211	152	231
May	2019	44,620	1,572	1,088	1,633	6,085	212	160	223
June	2019	42,781	1,599	1,063	1,653	5,927	211	158	227
July	2019	43,442	1,524	1,083	1,576	6,038	208	168	217
Aug	2019	42,335	1,509	1,079	1,551	5,841	202	164	212

GTA: Greater Toronto Area; ICU: intensive care unit; IQR: inter-quartile range. We used the minimum and maximum from the interquartile range for **Figure 3** in the main text.

Table A4. Distribution of acute care (hospital) admissions and ICU admissions in the GTA by hospital, from March 1 to August 30, 2019

	GTA total	St. Michael's Hospital			St. Joseph's Health Centre			Sunnybrook Health Sciences Centre		
		N	%	95% CI	N	%	95% CI	N	%	95% CI
Total number of inpatient admissions during the time-period	259,840	11,805	4.543	4.462, 4.626	10,325	3.974	3.897, 4.051	16928	6.515	6.417, 6.614
Total number of ICU admissions during the time-period	35,479	3,078	8.676	(8.372, 8.988)	814	2.294	(2.139, 2.457)	3,694	10.412	10.079, 10.753

CI: confidence interval; GTA: Greater Toronto Area; ICU: intensive care unit.
Note that Sunnybrook Health Sciences was not included in the analyses presented in the study.

1.6. Data on prevalent (inpatient census) in non-ICU, medicine, and ICU at St. Michael's Hospital and St. Joseph's Health Centre

We received aggregate estimates from Decision Support at each of the two hospitals on the median and IQR (inter-quartile range) of daily census of patients cared for in non-ICU and ICU beds between March 1 and May 30, between 2014 and 2019 inclusive. Each hospital also provided their respective bed capacity. We used the median estimate as the basis for **Main Text Figures 4-5**, and in estimates for Table 2 surrounding number of non-ICU and ICU beds required to remain within capacity.

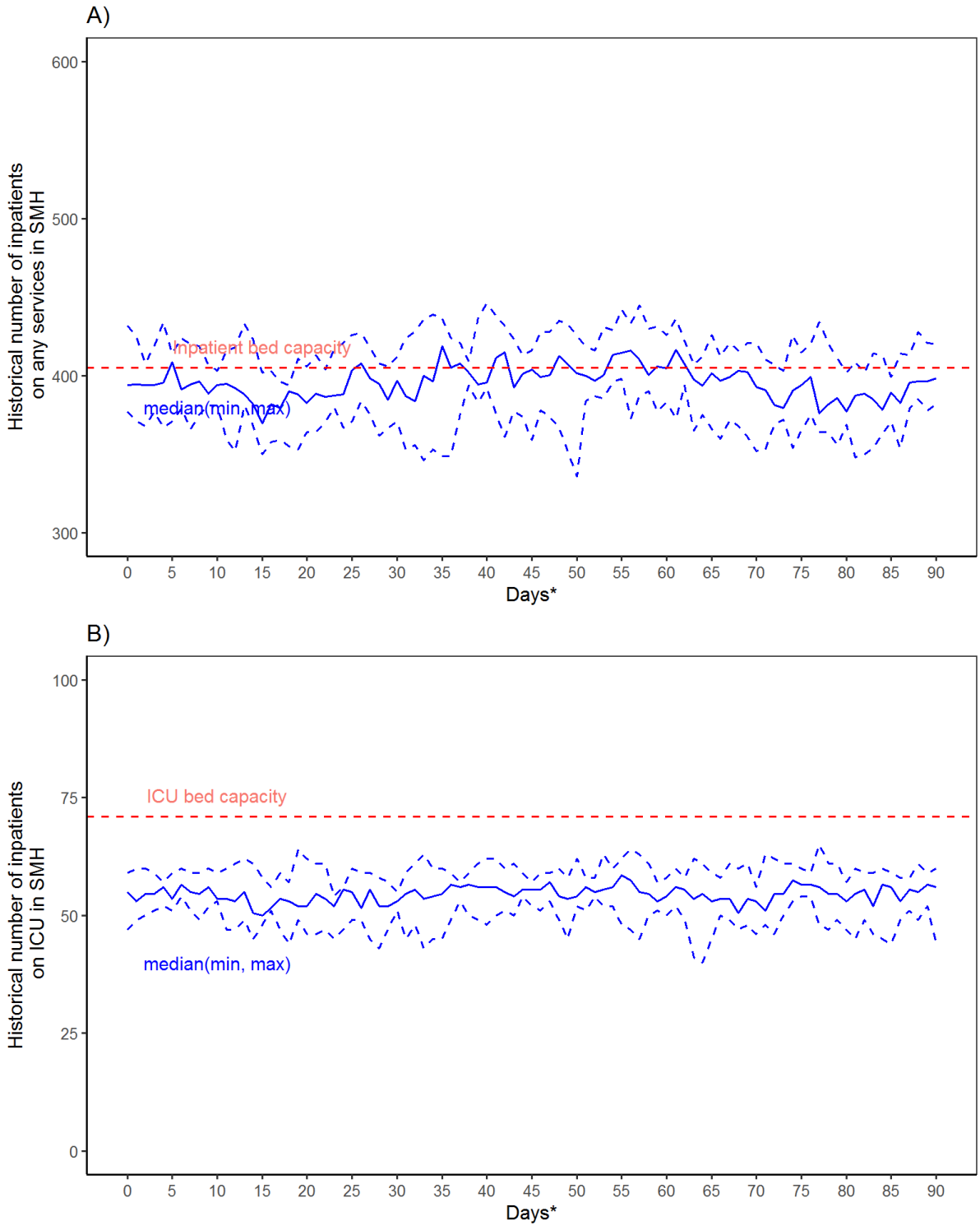


Figure A4. Baseline (2014-2019) daily census for non-ICU (A) and ICU (B) inpatients at St. Michael's Hospital using March to May for the 90 day period. The dashed red line indicates each hospital's bed capacity.

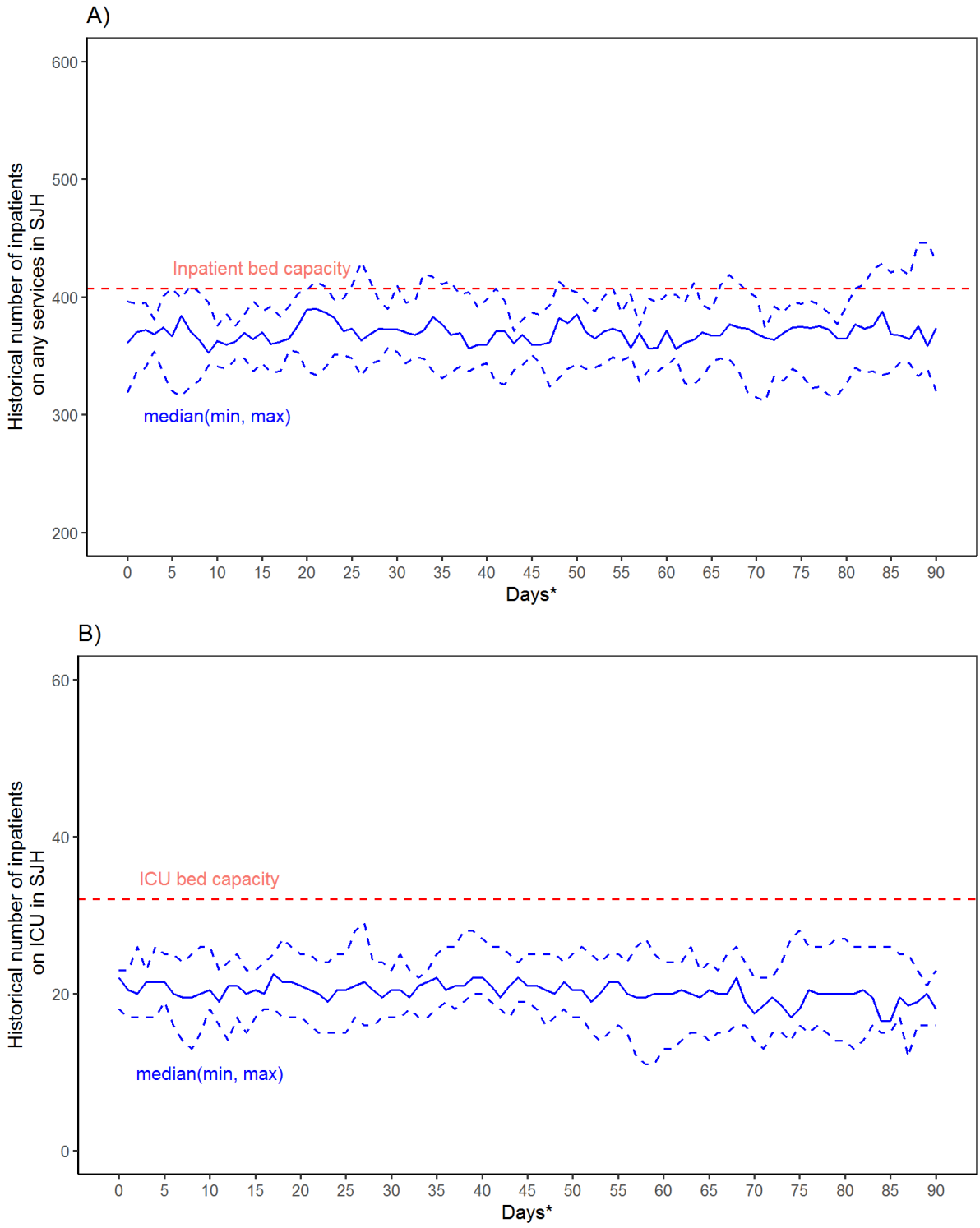


Figure A5. Baseline (2014-2019) daily census for non-ICU (A) and ICU (B) inpatients at St. Joseph's Health Centre using March to May for the 90 day period. The dashed red line indicates each hospital's bed capacity.

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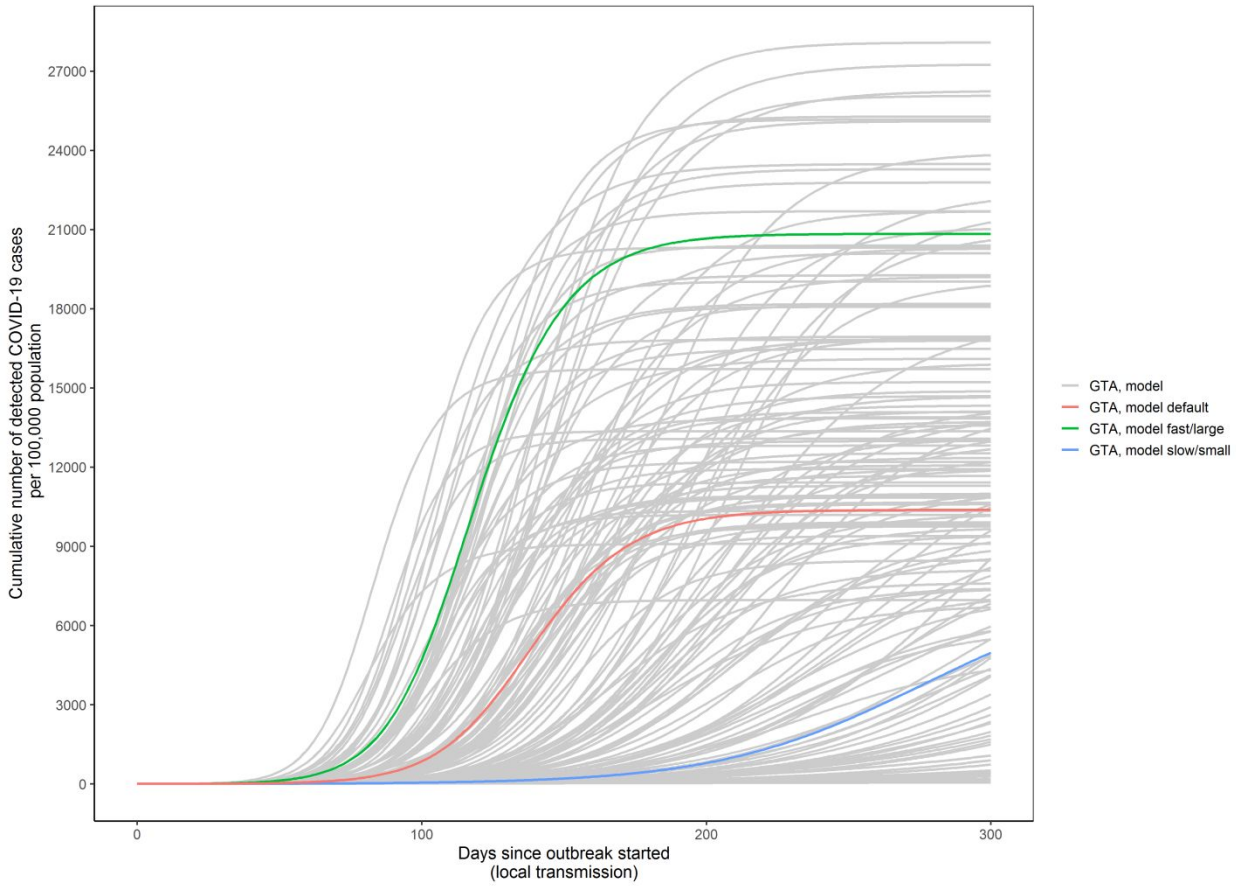
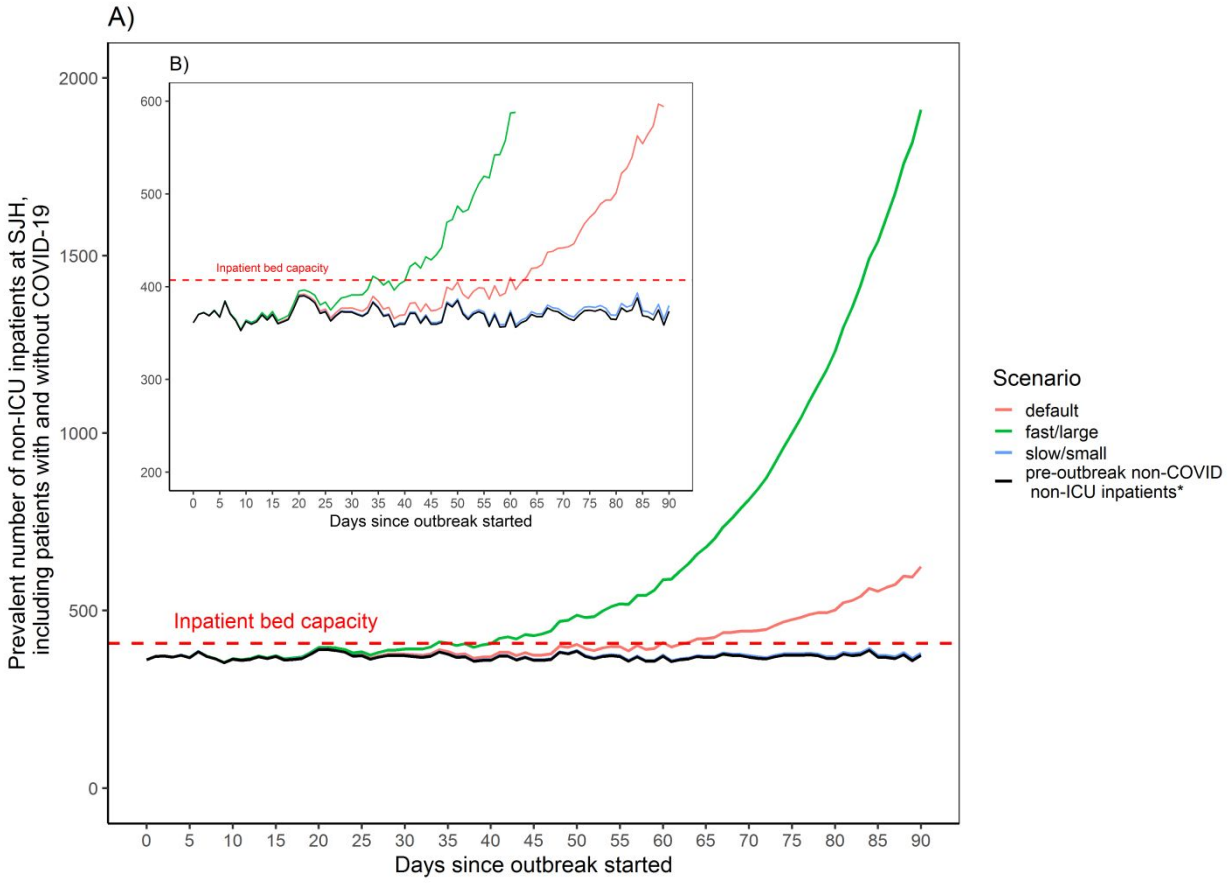
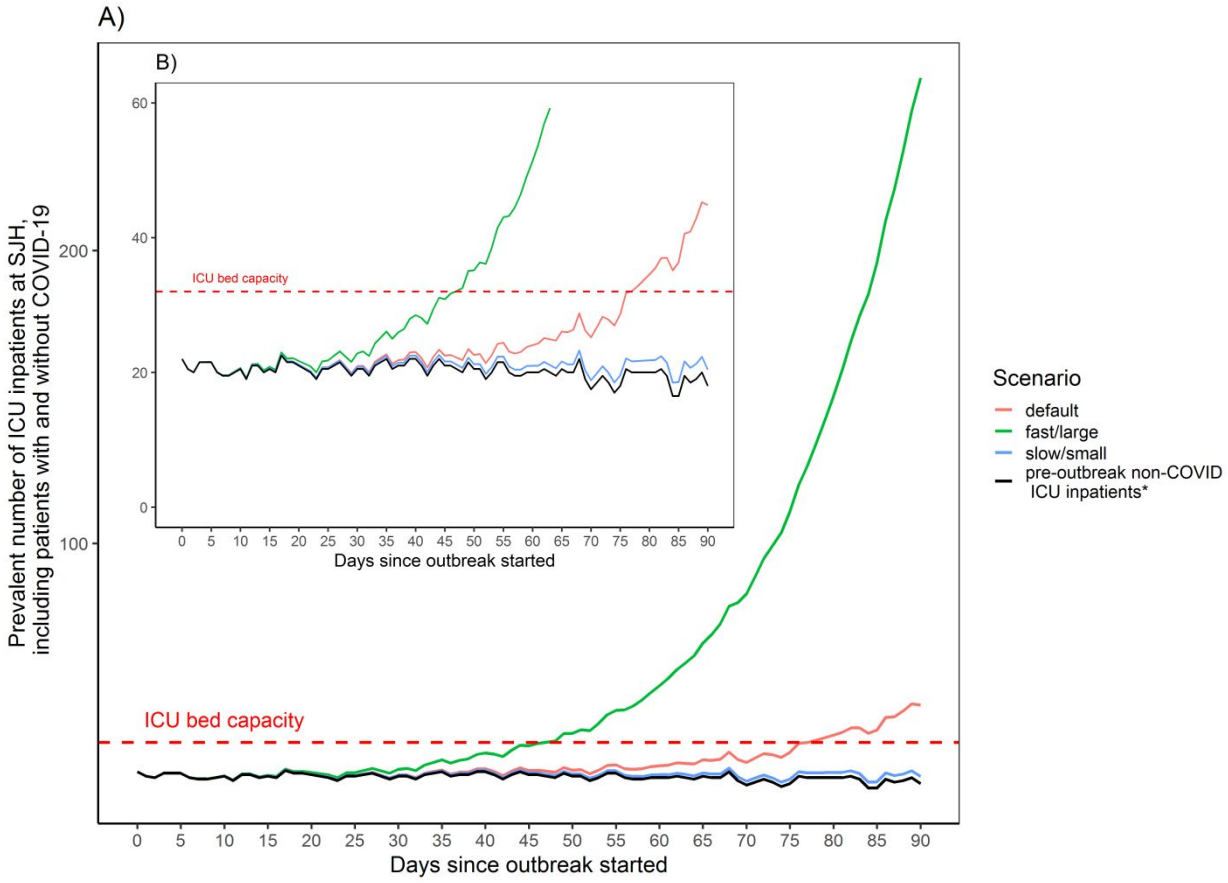


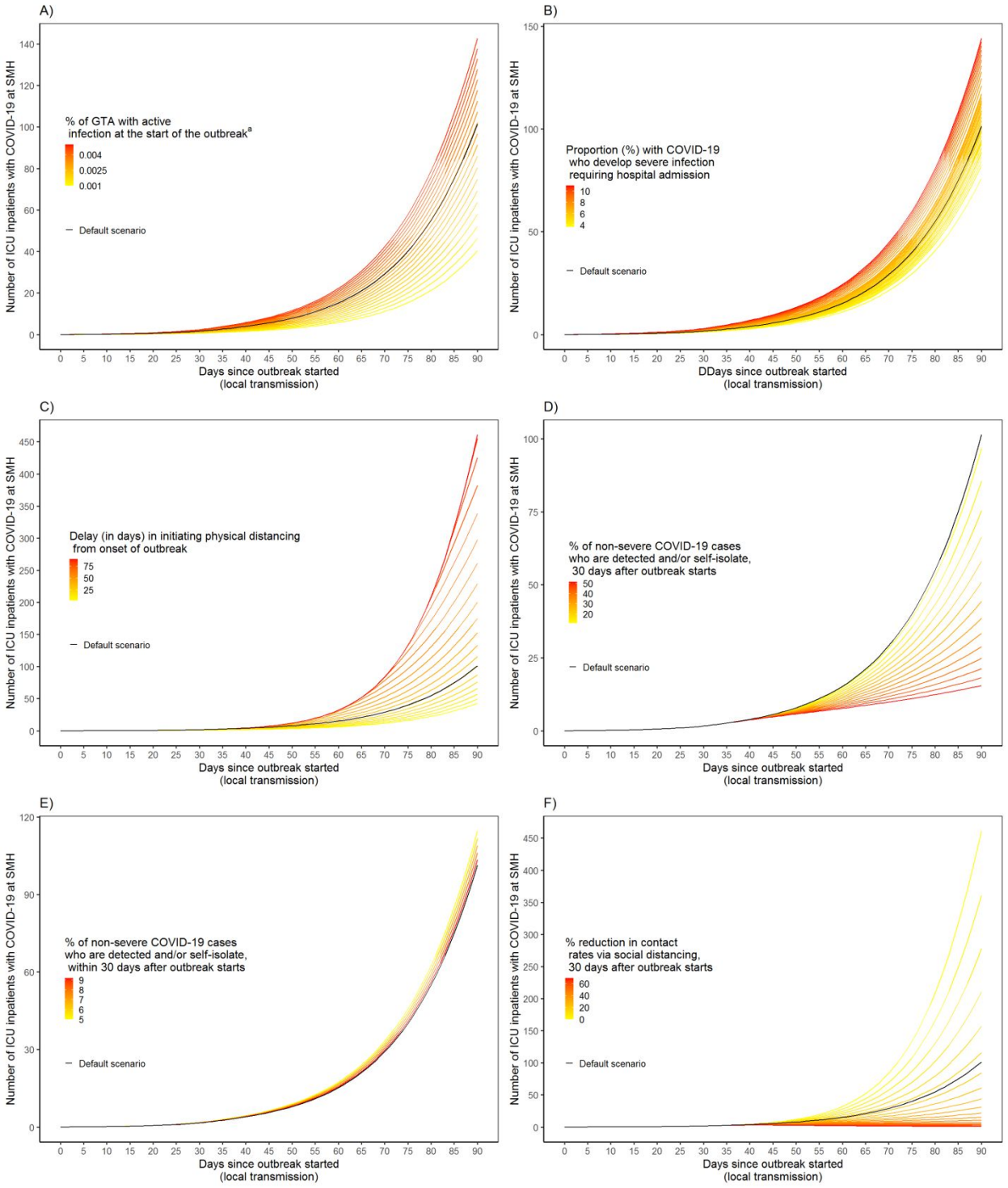
Appendix 2 Figure 2.1. Cumulative detected cases per 100,000 population across simulated epidemic scenarios. Model outputs from the sampled range of parameters in Table 1 which meet the model constraints are shown for detected cases as solid lines. The model output for the fast/large epidemic is shown in green and slow/small epidemic in blue, selected as the upper and lower quartile of peak incidence, respectively, within the first 300 days. The default (solid red line) depicts the default scenario (Table 1). Simulated timeline begins at the start of the 'seeding' of the population with 0.0011-0.0048% of the population already infected with SARS-Cov-2. For observed data, we define outbreak started when 3 confirmed cases were observed.

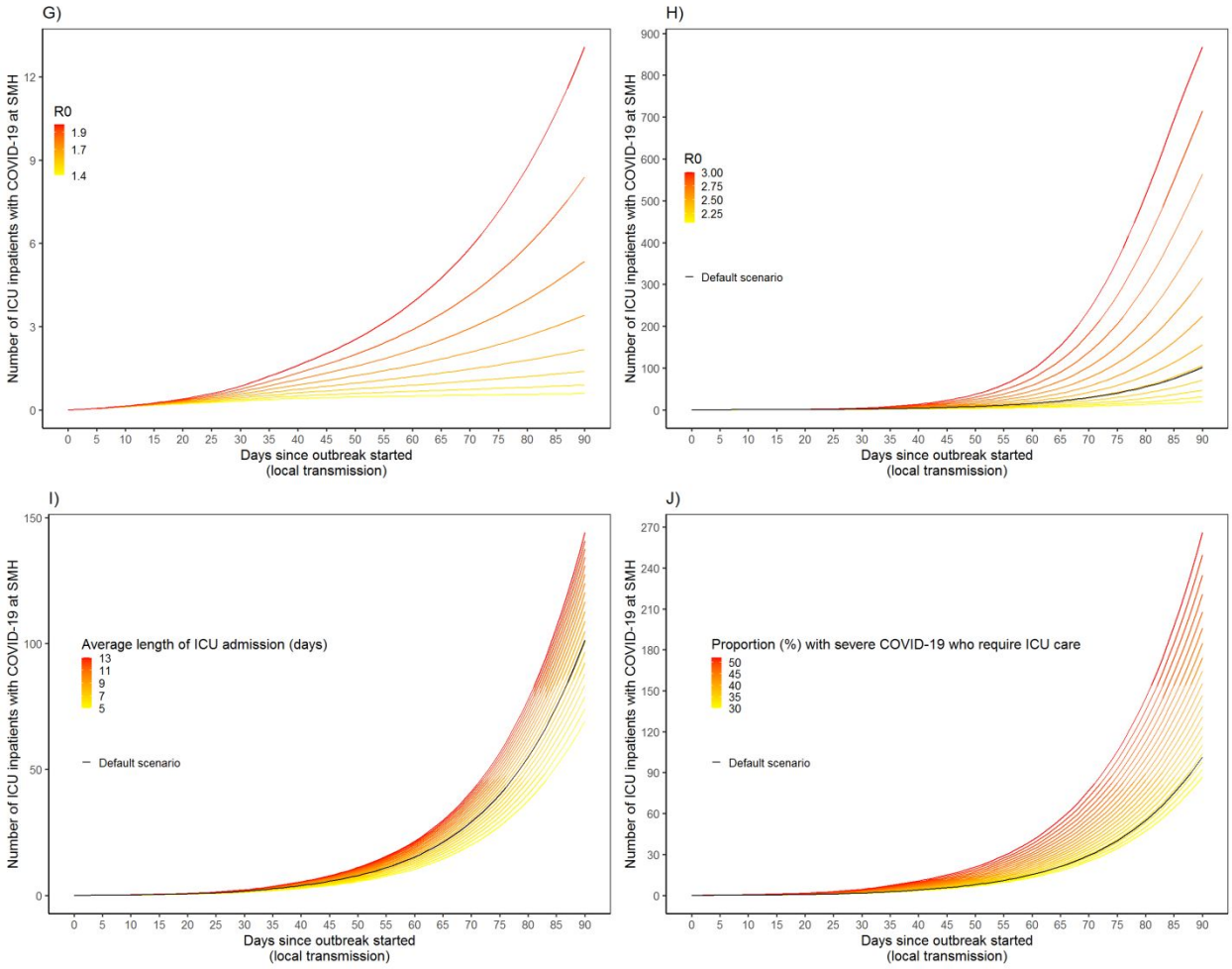


Appendix 2 Figure 2.2. Estimated surge and capacity for non-ICU hospitalization at St. Joseph's Hospital in the Greater Toronto Area. (A) Modeled number of non-ICU inpatients (including inpatients with and without COVID-19) and corresponding pre-outbreak baseline (non-COVID) number of non-ICU inpatients per day over 90 days. *Estimated by the median number of non-ICU inpatients at SJH between March – June, 2014-2019. (B) Same information as (A) but the y-axis ranged between 200-600. Estimates assume that distribution of non-ICU hospital admissions for patients with COVID-19 follows the pre-outbreak catchment of all non-ICU admissions across acute care hospitals in the Greater Toronto Area (March – August 2019), such that SJH receives 4.0% of all non-ICU hospital admissions. Our use of observed data on hospital-specific non-ICU admissions during March-June (black line) are not meant to indicate a start-date of the outbreak as March 1. All three scenarios (default, fast/large, and slow/small) assume that physical distancing started on day 30 and reduced contact rates by 20%, but has not increased nor decreased; and that the proportion of individuals with non-severe COVID-19 who self-isolate (e.g. via diagnosis of confirmed/suspected COVID-19) has not changed over the course of the epidemic. Abbreviations: ICU: intensive care unit; SJH: St. Joseph's Hospital.

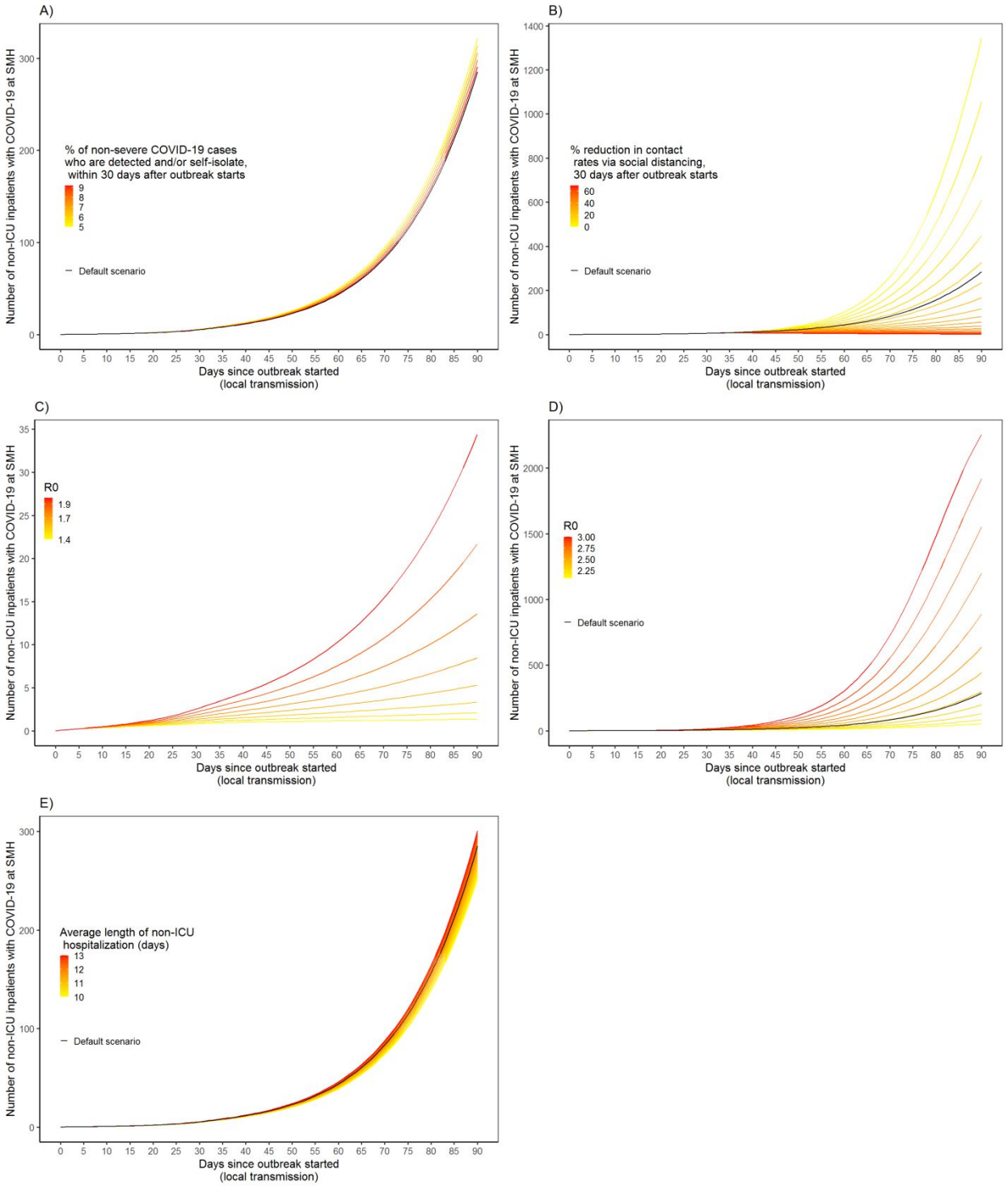


Appendix 2 for Figure 2.3. Estimated surge and capacity for ICU care at St. Joseph's Hospital (SJH) in the Greater Toronto Area. (A) Modeled number of ICU inpatients (including inpatients with and without COVID-19) and corresponding pre-outbreak baseline (non-COVID) number of ICU inpatients. *Estimated by the median number of ICU inpatients at SJH between March – June, 2014-2019). (B) Same information as (A) but the y-axis ranged between 0-60. Estimates assume that distribution ICU admissions for patients with COVID-19 follows the pre-outbreak catchment of all ICU admissions across acute care hospitals in the Greater Toronto Area (March – August 2019), such that SJH receives 2.3% of all ICU hospital admissions. Our use of observed data on hospital-specific ICU admissions during March-June (black line) are not meant to indicate a start-date of the outbreak as March 1. All three scenarios (default, fast/large, and slow/small) assume that physical distancing started on day 30 and reduced contact rates by 20%, but has not increased nor decreased; and that the proportion of individuals with non-severe COVID-19 who self-isolate (e.g. via diagnosis of confirmed/suspected COVID-19 or without) has not changed over the course of the epidemic. Abbreviations: ICU: intensive care unit; SJH: St. Joseph's Hospital.


A)
Number of ICU inpatients with COVID-19 at SMH
% of GTA with active infection at the start of the outbreak[a]
0.004
0.0025
0.001
Default scenario
Days since outbreak started (local transmission)
B)
Number of ICU inpatients with COVID-19 at SMH
Proportion (%) with COVID-19 who develop severe infection requiring hospital admission
10
8
6
4
Default scenario
DDays since outbreak started (local transmission)
C)
Number of ICU inpatients with COVID-19 at SMH
Delay (in days) in initiating physical distancing from onset of outbreak
75
50
25
Default scenario
Days since outbreak started (local transmission)
D)
Number of ICU inpatients with COVID-19 at SMH
% of non-severe COVID-19 cases who are detected and/or self-isolate, 30 days after outbreak starts
50
40
30
20
Default scenario
Days since outbreak started (local transmission)
E)
Number of ICU inpatients with COVID-19 at SMH
% of non-severe COVID-19 cases who are detected and/or self-isolate, within 30 days after outbreak starts
9
8
7
6
5
Default scenario
Days since outbreak started (local transmission)
F)
Number of ICU inpatients with COVID-19 at SMH
% reduction in contact rates via social distancing, 30 days after outbreak starts
60
40
20
0
Default scenario
Days since outbreak started (local transmission)



Appendix 2 for Figure 2.4. One-way sensitivity analyses using default epidemic scenario for prevalence of ICU inpatients with COVID-19 at St. Michael's Hospital. The influence of (A) seeding (proportion of population already infected with COVID-19 just at the start of the outbreak); and (B) clinical severity (proportion of individuals infected with COVID-19 who require hospitalization); (C) earlier or later initiation of physical distancing (from start of outbreak to 60 days after outbreak started); (D) proportion of individuals with non-severe COVID-19 who are diagnosed and/or self-isolate, 30 days after outbreak starts (e.g. due to increase capacity in testing in the community); (E) proportion of individuals with non-severe COVID-19 who are diagnosed and/or self-isolate; within 30 days since outbreak starts; (F) proportion reduction in contact rates via social distancing, 30 days after outbreak starts (e.g. due to increase capacity in testing in the community); (G) R0 (1.4-1.9); (H) R0 (2.0-3.0); (I) average length of ICU admission (days); and (J) proportion of individuals with severe COVID-19 who require ICU care. Note that the y-axis scales for figures are different. Abbreviations: ICU: intensive care unit; SMH: St Michael's Hospital; GTA: Greater Toronto Area.



Appendix 2 for Figure 2.5. One-way sensitivity analyses using default epidemic scenario for prevalence of non-ICU inpatients with COVID-19 at St. Michael's Hospital. The influence of (A) proportion of individuals with non-severe COVID-19 who are diagnosed and/or self-isolate, within 30 days since outbreak starts; (B) proportion reduction in contact rates via social distancing, 30 days after outbreak starts (e.g. due to increase capacity in testing in the community); (C) R0 (1.4-1.9); (D) R0 (2.0-3.0); and (E) Average length of non-ICU hospitalization (days). Abbreviations: ICU: intensive care unit; SMH: St Michael's Hospital; GTA: Greater Toronto Area.

Online Appendix 2 Tables

Appendix 2 - Table 2.1. Comparison of parameter values for selected epidemic scenarios.

		Scenario*		
	Unit	Fast/Large	Default	Slow/Small
Epidemiological				
R0	Number	2.5	2.4	1.8
Incubation period	Days	4.7	5.2	5.6
Duration of latent infection	Days	1.6	2.0	2.8
Duration of subclinical infectiousness	Days	3.1	3.2	2.9
Duration of symptomatic infectiousness	Days	6.0	7.0	7.0
Duration of infectiousness period	Days	9.1	10.2	9.9
Serial interval	Days	6.2	4.4	5.2
Initial seeding	% of total population	0.0040	0.0032	0.0026
Clinical				
Proportion diagnosed with COVID-19 who required hospitalization	%	19.6	10.0	9.2
Proportion infected with COVID-19 who were diagnosed	%	53.2	55.0	57.8
Proportion infected with COVID-19 who required hospitalization	%	10.4	5.5	5.3
Proportion hospitalized who require ICU care	%	35.9	33.0	46.4
Duration of hospital stay	Days	12.1	12.0	12.1
Duration of ICU stay	Days	7.2	8.0	10.0
Case-fatality proportion among those in ICU care	%	22.6	38.0	34.8

* The fast/large epidemic and slow/small epidemic were selected as the upper and lower quartiles of peak incidence, respectively, within the first 300 days. The default scenario used the default parameter set as shown in Table 1.
Abbreviation: ICU: intensive care unit

Appendix 2 Table 2.2. Peak number of daily incident and prevalent non-ICU and ICU inpatients with COVID-19 within 300 days of a simulated outbreak in the Greater Toronto Area

	Among selected scenarios**			Across 153 constrained epidemics***		
Measures	Fast/Large	Default	Slow/Small	Median	Lower Quartile	Upper Quartile
Peak number of daily new hospital admissions*	8638	3865	1032	3445	1348	5660
Peak number of daily new ICU admissions	4962	1802	976	2112	967	3952
Peak number of non-ICU inpatients	74988	32368	7152	21853	10189	38502
Peak number of ICU inpatients	25733	7418	5551	7739	2454	17651
Proportion of population infected by day-300, %	71.6	71.1	33.7	66.5	35.6	77.9

*All new hospital admissions, which include patients who remain in non-ICU beds, and patients who are subsequently admitted to the ICU.
**The fast/large epidemic and slow/small epidemic were selected as the upper and lower quartiles of peak incidence, respectively, within the first 300 days. The default scenario used the default parameter set as shown in Table 1.
***Among 200 simulated epidemics, 153 met the constraints using the observed data for Lombardy, Italy and Hong Kong, China (corresponding data points at day 30 since outbreak started were used as upper and lower bounds, respectively to constrain the epidemics).
Abbreviation: ICU: intensive care unit.