COVID-19 Epidemic in Mumbai: Long term projections, full economic opening, and containment zones versus contact tracing and testing

TIFR Covid-19 City-Scale Simulation Team

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I. Summary

Mumbai, amongst the most crowded cities in the world, has witnessed the third largest number of cases and the largest number of deaths among all the cities in India. The first case in Mumbai was detected on 11 March 2020, and the first fatality was recorded on 17 March 2020. Currently, as of 31 August, 2020, Mumbai has reported 146,947 cases and 7,690 fatalities, thus contributing disproportionate share to India's tally of 3.77 million reported cases and 66,491 deaths. Mumbai, along with the rest of India has been in a lockdown since March 25, 2020. Initially imposed for three weeks, this lockdown was extended in Mumbai and other parts of India till May 17, 2020. Thereafter, Mumbai has seen gradual relaxations in population movement. In particular, in the latest "Mission Begin Again" order dated 31st August 2020 [1], the Government of Maharashtra has allowed 20% attendance in workplaces.

As per the release by the government, the Indian economy contracted by 23.9% in the first quarter of the fiscal year 2020-21. Given the large economic toll on the country from the lockdown and the related restrictions on mobility of people and goods, swift opening of the economy especially in a financial hub such as Mumbai becomes critical. However, opening up of Mumbai is crucially linked to opening its crowded public transit systems, especially the crowded suburban trains. Too swift an opening may lead to a sudden increase in the spread of the epidemic leading to a 'difficult to manage' second wave of hospitalisations.

Fortunately, the curve of medical indicators for Mumbai such as hospitalisations, critical patients, reported cases and fatalities at any time, has begun to stabilize or 'flatten' over the months of June and July and appears to be further reducing in August. This flattening is corroborated by the high degree of prevalence found in Mumbai, especially in slums, by the Mumbai Sero-Survey [2]. These observations allow the city room to further open up. In this short report, we use our IISc-TIFR agent based simulator described in detail in [3] to develop long term projections for Mumbai under realistic scenarios related to Mumbai's opening of the workplaces or equivalently the economy, and the associated public transportation through local trains and buses.

These projections were developed taking into account a possible second wave if the economy and the local trains are fully opened either in mid-September or on November 1. The impact on infection spread in Mumbai if the schools and colleges open on January first week 2021 is also considered. Our conclusion, based on our simulations, is that the impact of fully opening up the economy on November 1 is easily manageable with the current medical infrastructure. Schools and colleges opening in January do not lead to excessive increase in infections.

Further, our simulations suggest that by around December 2020 and January 2021, the prevalence (fraction of the population infected) can be seen to be stabilising close to 75% in slums and 50% in non-slums. This stabilisation and high prevalence indicates that Mumbai city may have more or less reached "herd immunity" by then and further new infections in the city will be substantially reduced.

In these simulations we also conduct counterfactual experiments where the containment efforts as well as the contact tracing and testing efforts are varied and their impact on the health indicators is measured. Our simulations suggest that containment efforts do a better job of slowing infection spread compared to increasing the contact tracing and testing efforts. Increase in the latter leads to only marginal improvement in slowing the infection.

Below, we list some policy recommendations for opening up the workplaces and schools and colleges in Mumbai that incorporates above considerations.

A. *Policy Recommendations*

- We recommend gradual opening of the workplaces so that the increase in infections that may result from increased occupancy in local trains and other public transport is manageable. We recommend the following phased opening of the workplace: 33% in September, 50% in October and finally 100% in November. Schools and colleges may be opened by first week of January 2021. As mentioned earlier, our simulations suggest that the resulting second wave from this opening up is minimal.

- Social distancing in public transport, staggering of office times, use of shifts to the extent feasible is recommended.
- The opening up of the workplaces should be carefully monitored and may be adjusted based on observed infections.
- Prevailing hygiene measures such as mandatory use of masks/face-covers, encouragement of regular hand-hygiene, regular disinfection of “high-touch surfaces” in trains and workplaces [4] etc. should continue as before.
- Our analysis of containment zones vis-a-vis contact tracing and testing suggests that wherever feasible and when the economic costs are not prohibitive, containment in regions where infection is seen to be present is a desirable option to slow the infection spread.

In addition to the various modeling assumptions listed in our previous reports [3], [5], our recommendations rely on two important assumptions.

1) Our first assumption is that the population, by and large, will continue to observe social distancing precautions including wearing of masks. This could change as public perception of risk changes over time. This may lead to increase in infections not accounted for in our projections.
2) Our second assumption is that the reinfection probability is sufficiently small for that population of Mumbai that it can be ignored in opening up of the city. We note that cases of reinfection have recently been reported. However, the number of such reports continues to be very few. If this changes and reinfection happens to a non-negligible proportion of the population, then our projections become less valid.

Caveats: We emphasize that our simulator is intended primarily as a tool for comparing the effectiveness of different non-medical interventions to assist decision making. In particular, the simulator, due to the inherent model uncertainty, is not intended as a tool for predicting absolute numerical values of COVID-19 cases. In our informal view (which is difficult to validate scientifically), a confidence interval of $\pm$ 20% to 30% around the projected numbers may be reasonable to capture the model uncertainty. This number may be larger when estimates with small values are considered. On the other hand, the statistical error due to the random noise in the simulations is much smaller and is easily controlled. We also recognize that many of the non-pharmaceutical interventions considered in our study, especially when they remain implemented over a long duration, may lead to important social and economic concerns and consequences, beyond their effect on the evolution of the epidemic. The modelling of such effects still remains beyond the scope of our simulator.

Similar to our previous report, we emphasize that this report has been prepared to help researchers and public health officials understand the effectiveness of social distancing interventions related to COVID-19. The report should not be used for medical diagnostic, prognostic or treatment purposes or for guidance on personal travel plans.

II. Towards fully opening Mumbai

Greater Mumbai (consisting of Mumbai and Suburban Mumbai) has a population of about 1.24 crores (12.4 million) and a population density of roughly 21,000 per km^2 [6], [7] making it one of the densest cities in the world[1]. Further, about 53% [8] of Mumbai lives in cramped dwellings with shared sanitation facilities where the population density may be 5 to 10 times larger than other parts of the city. In addition, crowded suburban trains are the lifeline of the city where the suburban railway system serves more than 78 lakh (7.8 million) passenger trips daily, in normal times. It is generally believed that the infection spreads faster in denser areas, due to increased contacts in these areas. Given these factors, the public health threat in Mumbai is particularly acute. The importance of modelling the effect of infection spread arising from the gradual opening and relaxation of lockdown measures, for a city like Mumbai, cannot then be over-emphasized. We model the spread of infection in the city using our IISc-TIFR agent-based city simulator [3]. For completeness, we briefly review it below.

Agent-based city simulator (ABCS): As described in detail in [3], our agent-based simulator creates a synthetic model of about 1.24 crore (12.4 million) residents of Mumbai that matches the city population ward-wise, and matches the numbers employed, numbers in schools, commute distances, etc. This is done by suitably populating households, schools, and workplaces with people. Several interaction spaces including households, local communities, schools, workplaces, trains, etc. are then modelled to realistically capture the spread of infection. The synthetic city is then seeded with infections to match the observed fatalities till April 10. The infective individuals expose the susceptible individuals to the disease through their interactions in the various interaction spaces. The disease then incrementally evolves in time. The tool helps keep track of the number infected in the city as well as the disease progression within an infected individual. A person infected by the disease may remain asymptomatic and recover, or may develop symptoms. A symptomatic person may recover or may develop severe symptoms and be hospitalised. A patient hospitalised may recover or

[1]Some of the discussion in the Introduction first appeared in [5]

may become critical. A critical patient may recover or may become deceased. The disease progression parameters are based on [9].

A. Scenarios considered

In this work we report the following scenarios:

- **Long term forecasts:** We develop long term forecasts till March 15, 2021 under the following four scenarios:
  - Containment effort set at 75% and at 60%. Exact modelling of containment effort relies on the modelling feature 'neighbourhood containment zones' introduced in [3] and is discussed later in Section III.
  - Train infection levels are set at normal $\beta_T = 0.19 \times \beta_H$ (see [5] for detailed calculations to arrive at this number; that report also discusses the household transmission parameter β_H and the rationale that relates it to β_T. The value of β_H used is calibrated primarily to fatality data, and is given in Figure 1.), as well as the more pessimistic and higher $\beta_T = 0.30 \times \beta_H$.

  The workplace attendance is a good measure of economic activity. It is set in our model as follows: Lockdown till May 17. Mobility to workplaces set at 5% from May 18 to May 31. In June this is set at 15% and it increases to 25% in July. It is set at level 33% in August and thereafter from September onwards we keep it constant at the level 50%. The developed model is validated by comparing the model projections with the observed health data, that is, observed number of fatalities, hospitalisations, critical cases and recorded cases. The methodology to aid in measuring recorded cases and related contract tracing in our model is introduced in [3]. This modelling feature is further discussed in Section III. In our experiments, keeping the workplace occupancy fraction constant at 50% from September onwards provides us a base case that helps better appreciate the changes that result from the other interventions. As in [5], in all our simulations we continue to assume that 60% of households are compliant in residential, relatively low density areas (non-slums), while 40% of households are compliant in slums or high density areas.
- **Fully operational economy:** We consider the following three scenarios: The workplaces fully operational on September 16, workplaces fully operational on November 1, and workplaces fully operational on November 1 and schools and colleges opening on January 1. Fully opening workplaces or the economy implies that the trains are back to the capacity as in normal pre-covid times.

- **Containment zones and contact tracing and testing** are regarded as two important policy tools available to decision makers in slowing the epidemic spread. Our small network framework (introduced in [3]) through the neighbourhood cells allows us to model neighbourhood containment efforts with reasonable accuracy. Further, the small network framework with the introduction of the community of friends and neighbourhood community, allows us to plausibly model the contact tracing and testing efforts. As mentioned earlier, these are discussed in Section III. Through our model we evaluate the performance of containment efforts by measuring the health indicators as a function of varying containment efforts. We similarly evaluate the the impact of varying level of contact tracing and testing efforts on the health indicators. While containment zones are relatively easier to administer compared to contact tracing and testing, our simulations suggest that the former may also be more effective in slowing the spread of the infection in the city. A caveat to keep in mind is that containment zones lead to restricting movements of relatively large number of people, and so may come at a significant economic cost.

III. SMALL NETWORKS, CONTAINMENT AND CONTACT TRACING

A. Smaller networks

As detailed in our previous report, each of the interaction spaces is further broken down in subnetworks that corresponds to most of the interactions that an agent has within that interaction space (for instance, 90% of an agent's interactions in the workplaces are within their "project" subnetwork). The subnetworks are listed as follows.

As in the earlier report [3], the contact rates are calibrated to match the observed growth of fatalities, and to have roughly equal contribution of infections from the household, community and workplace networks (including the subnetworks) in the "no-intervention" scenario.

B. Containment strategy

While in [5] the containment zones were modelled at the ward level for computational ease, in the current implementation we aim for more accuracy through a finer and more accurate model of containment. In particular, we model containment at a neighbourhood cell level. Recall that our synthetic city is divided into a grid of square cells where length of each cell is 176 meters. Containment effort is modeled as an increasing adaptive function of the active hospitalisations observed in the neighbourhood cell. Number of hospitalisations is taken as the decision variable since it is easily observable as compared to tracking the

Subnetwork	Larger interaction space	Description
Project	Workplace	Clusters of size 3–10 (uniformly chosen)
Class	School	All students of a specific age
Neighbourhood	Community	Grid cells of side length 178 mts
Close friends	Community	2–5 households randomly chosen for each household

Interaction space	Comment	β value
Home	(calibrated)	2.08232
Workplace	(calibrated)	0.28393
Community	(calibrated)	0.02460
School	$2 \cdot \beta_{\text{workplace}}$	0.56786
Project	$9 \cdot \beta_{\text{workplace}}$	2.55537
Class	$9 \cdot \beta_{\text{school}}$	5.11074
Neighbourhood	$9 \cdot \beta_{\text{community}}$	0.2214
Close friends	$9 \cdot \beta_{\text{community}}$	0.2214

Figure 1: Interaction spaces, subnetworks and contact rates

number of positive cases in a cell, which may be harder to estimate accurately without extensive testing, and the two are highly correlated. The cell is incrementally closed as more number of hospitalisations are observed in it.

Specifically, suppose that the containment effectiveness (CE) =75% and there are 3,000 residents in a neighbourhood cell. Then, first hospitalisation leads to movement restriction of 25% internally amongst the residents as well as to and fro from the cell; second hospitalisation leads 50% movement restriction, and third hospitalisation onwards leads to 75% movement restriction. If, on the other hand, the neighbours in the cell are less than a thousand, then as long as there exists a hospitalised person in the cell, movement of every resident within the cell, as well as movements into and out of the cell are restricted by 75%.

More precisely, If containment effectiveness is set to a fraction y, and the neighbours in a cell equal n thousand, then every hospitalisation leads to y/n restriction in movement, and total movement restriction is capped at y. Thus, percentage of activity restriction (internally as well as in entering and leaving the cell), or containment effectiveness, is our control and we set it to

$$\min\left(hy/n, y\right),$$

where h denotes the number of people in the neighbourhood cell that are hospitalised[2].

C. Contact tracing

The simulator also has the ability to implement contact tracing. The contact tracing machinery can be briefly described as follows:

1) An individual that the simulator deems as a *hospitalised* case undergoes a COVID-19 test with some probability (specified by the protocol given in Figure 2). If the test turns out to be positive, this agent is deemed as a *hospitalised index case*. This hospitalised case is typically tested with probability 1, although later in Section VI when we evaluate medical statistics under different testing protocols, we allow this probability to take lower values of 0.66 and 0.8 as well.
2) When an *index case* is identified, a fraction of agents from their subnetworks (specified by the protocol) are quarantined and marked as *primary contacts*.
3) Each primary contact is tested with some probability (specified by the protocol). If the test is positive, then such agents are marked as *positive index cases*. The newly discovered *positive index cases* would additionally initiate contact trace around this agent like in the *hospitalised index cases*.

In the current implementation, 0.5% of the neighbourhood cell (which is 5 agents on average) and 100% of all other subnetworks are deemed as the agent's primary contacts. Furthermore, the testing probabilities in our current implementation are set to match a rough test positivity rate of 30% to 40%, which is the observed test positivity rate during the months of June and July in Mumbai [10].

[2]In our current implementation, the number of hospitalized cases *excludes* those who are currently in critical care facilities.

Subnetwork	Type of index case	Status of primary contact	Test probability
Household	Hospitalised	Symptomatic	1
	Hospitalised	Asymptomatic	0.45
	Positive	Symptomatic	1
	Positive	Asymptomatic	0.45
Project	Hospitalised	Symptomatic	0.5
	Hospitalised	Asymptomatic	0.225
	Positive	Symptomatic	0.25
	Positive	Asymptomatic	0.1125
Close friends	Hospitalised	Symptomatic	0.25
	Hospitalised	Asymptomatic	0.2
	Positive	Symptomatic	0.125
	Positive	Asymptomatic	0.06
Neighbourhood cell	Hospitalised	Symptomatic	0.25
	Hospitalised	Asymptomatic	0.2
	Positive	Symptomatic	0.125
	Positive	Asymptomatic	0.06

Figure 2: Testing protocol

IV. Simulation results

As in [5], in all our simulations, we set the compliance levels to 60% in residential or non-slum areas, and at 40% in high density or slum areas. This level of compliance with additional measures such a mask usage, case-isolation and home quarantine post lock-down, restriction on those above 65 to stay home, closed school and colleges match reasonably well the observed data on fatalities.

Further, accounting for the results of the Mumbai SeroSurvey [2], and in deviation from our earlier analysis in [5], we reduce the proportion of symptomatic population amongst those exposed to the Covid-19 disease to 40% from the earlier 66.67%. The model is recalibrated using this fraction.

A. *Long term projections*

We first discuss the long term projections. As mentioned earlier, we consider these under the workplace attendance scenario where after lockdown till May 17, there is 5% attendance from May 18 to May 31st. This increases to 15% attendance in June, 25% in July, 33% in

August and then 50% September onwards. These projections are developed till March 15, 2021 under the following four scenarios.

- The containment effectiveness kept at 75% as well as 60%.
- The infection rate from trains kept at $\beta_T = 0.19 \times \beta_H$ (recall that β_H corresponds to the household transmission parameter). This was derived as a plausible rate of infection in trains in [5]. To account for the uncertainty in such calculations, we also consider the more pessimistic setting of higher $\beta_T = 0.30 \times \beta_H$.

Since CE=0.60 and $\beta_T = 0.3 \times \beta_H$ report higher infections amongst the four settings, to err on the side of caution, we use these parameters for base data series for some of our calculations and for comparisons with reported data.

As in Reports [3] and [5], in our simulations, two synthetic cities are created that match the aggregate Mumbai demographic data. For each of the two cities we run 5 independent simulations. The reported results are the average of these ten runs.

In Figures 3a and 3b, we show the daily as well as the cumulative number of infections under the four scenarios. These results suggest that the growth of infections in Mumbai started to slow down from June. From December 1 onwards the number of new infections becomes very small indicating that by and large herd immunity has been reached by the city. Furthermore, this suggests that city will stabilize with about 7 to 8 million residents infected.

In Figure 4, we map the prevalence for all of Mumbai suggested by the model when CE is set to 0.60 and β_T is set at $0.3 \times \beta_H$. We also separately plot the prevalence for slums and non-slums. The salient observations are that herd immunity is reached at different level of prevalence in slums and non-slums. In slums this is attained at around 75%, while in non-slums the number is closer to 50%. The Mumbai SeroSurvey [2] suggested around 55% prevalence in slums and 14.5% prevalence in non-slums of the three wards of Mumbai that were sampled around the first two weeks of July. Our respective numbers on July 15 of 50% and 22% are not too far from theirs, and match them quite well on average (recall that as per our model and census 2011, 52.5% of Mumbai population resides in slums and the rest in non-slums).

Figure 5a shows the daily number of the hospitalised patients as per our model under the four scenarios. In Figure 5b, we compare our hospitalisation numbers to the hospitalisation numbers reported by BMC in their Dashboard [10]. The BMC dashboard reports Dedicated Covid Hospital (DCH) as well as Dedicated Covid Health Centre (DCHC) aggregated together and these are reported as hospitalisations under DCH and DCHC. We make the following adjustments to the data series from our model as well as from the BMC Dashboard to make the comparison between them more apples to apples.

1) As per personal communication with BMC, from mid-July onwards many of the hospital beds are taken up by patients coming from outside of Greater Mumbai (Greater Mumbai denotes the area that comes under the jurisdiction of BMC). These include patients coming from other areas in Mumbai Metropolitan Region (MMR) including Thane, Navi Mumbai and Vasai-Virar as well as from somewhat further regions such as Nasik. These are roughly estimated to equal 30% (based on feedback from a BMC official). To account for these, we increase our hospital patient projections by 30%, with the understanding that this increase is reasonable for comparison with observed data beyond mid-July.
2) The DCH and DCHC numbers reported by the BMC Dashboard include patients under ICU. In our model we report patients under ICU (critical patients) separately. Thus, we remove the ICU patients in the Dashboard data from the DCH and DCHC data.
3) Further, based on the snapshot data provided by BMC on August 1 and August 20, we inferred that about 13% of patients in DCH and DCHC are asymptomatic. The disease progression data in our model is taken from [11] and [9], and here hospitalised patients correspond to those with serious symptoms. Thus, to compare our projections with the observed data, we further reduce the DCH and DCHC reported numbers by 13%.

It can be seen from Figure 5b that with the above corrections, post mid-July, our projections are reasonably close to the adjusted DCH and DCHC numbers.

In Figure 6a, the projected daily number of the critical cases under the four scenarios are shown. Again, to compare with the Mumbai ICU numbers as per the BMC Dashboard, we scale our numbers by 41% in Figure 6b. These again our based on a snapshot input provided by BMC where 41% of the critical beds used by the Mumbai population were in use by population from outside the city. Here too, the match between the adjusted model and data after mid-July appears reasonable. From May 27 to June 16 the occupancy of reported ICUs was seen to be above 98% as per the BMC Dashboard (except on May 29, when it was 97%). This may at least partially explain why the model numbers for critical cases in this period are much higher than the actual numbers.

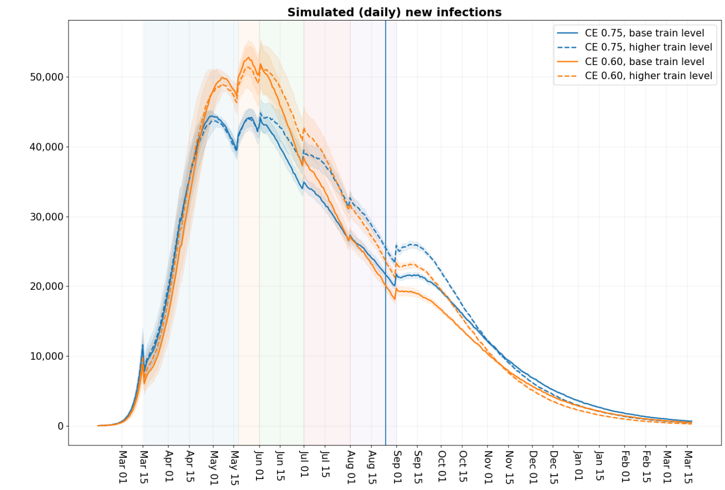
Figure 7a shows the projected fatalities based on our model and compares them to the fatality data as reported by BMC through their Dashboard. Figure 7b shows cumulative number of fatalities as a function of time. As pointed out in earlier reports [3] and [5], in our model the key transmission rates are calibrated to primarily match the initial observed fatality data in Mumbai as well as in the rest of India. Further, the compliance parameters used in the model are fine tuned so that the model fatalities are close to the reported fatality data (as reported by BMC through their Dashboard [10]). As evident from the two figures, the match between the model generated fatality and the reported fatality data appears to be quite good. Few points are in order.

- BMC in mid-June had updated the reported deaths data. Figure 7b shows both the original and the updated reported fatality data. Observe, that our model (the data series corresponding to CE 0.60 and higher train β_T level) slightly underestimates this series from mid-May to mid-June. One reason for this may be that while in our model there is no limit on ICUs for critical patients, the city of Mumbai did observe this shortage around that period.
- Our model reports higher number of deaths (under CE 60%, and higher β_T value) compared to the reported from July onwards. This may be partially explained by the fact that around mid-June (see, https://timesofindia.indiatimes.com/city/mumbai/maharashtra-stops-testing-bodies-says-will-ease-painful-delays-for-kin/articleshow/76474747.cms) BMC stopped testing dead bodies for covid.

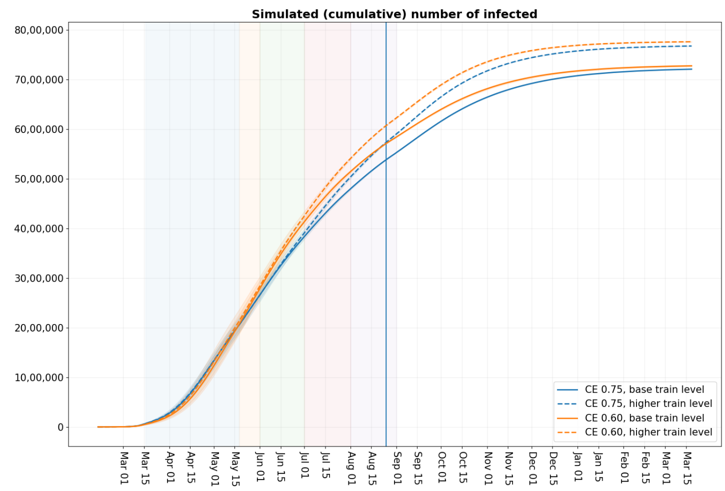
A broad conclusion suggested by our model is that the fatalities in the city will stabilize within 11,000 to 12,000 by March 2021. As we observe later, under more realistic setting where the economy is fully operational at Nov. 1, 2020, the overall projected fatality number for the city further increases a little.

In Figure 8a, we see that our contact testing and tracing strategy detects cases that fairly closely matches the observed cases from mid-May onwards until the last ten days of August. However, it substantially overestimates the cases up to mid-May. This may reflect a change in contact tracing and testing strategy adopted in Mumbai around that time. Figure 8a suggests that reported cases in Mumbai would reduce to around 500 per day by mid October. The rise in reported cases in the last ten days of August may reflect a new strategy by the administration involving increased testing amongst the population.

In Figure 8b we see the projected cumulative curve for reported cases. As mentioned above, the model overestimates the actual reported cases early on but thereafter the projected curves and the actual reported cases curve appear to have similar shape.



(a) Daily new infections under the workplace opening schedule 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% September onwards.



(b) Cumulative infection growth under the workplace opening schedule 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% September onwards. Under this schedule as per simulations the city stabilizes with 7 to 8 million of the population infected.

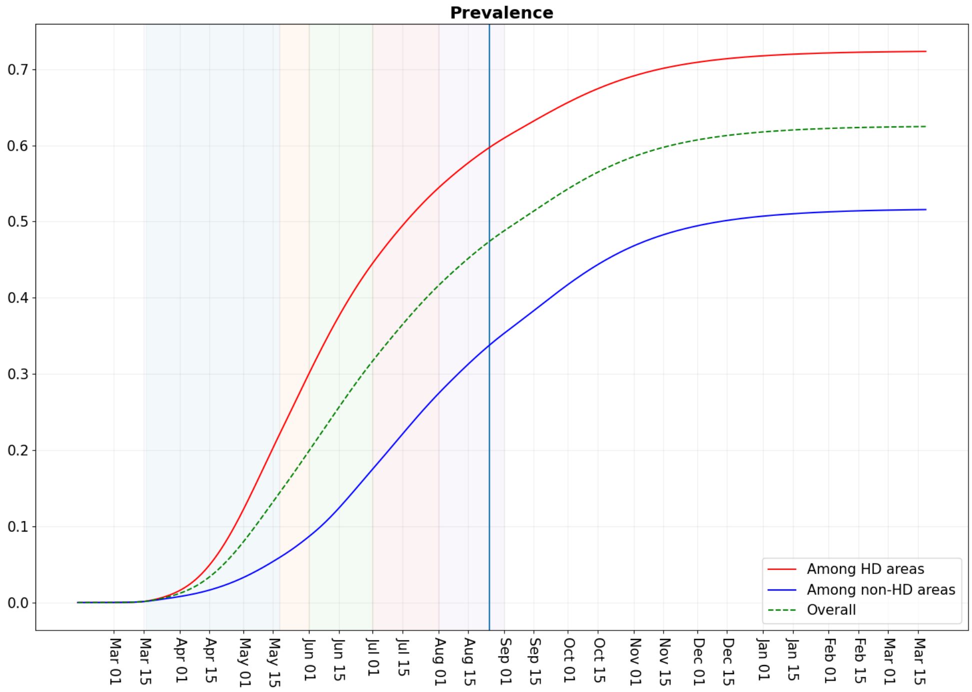
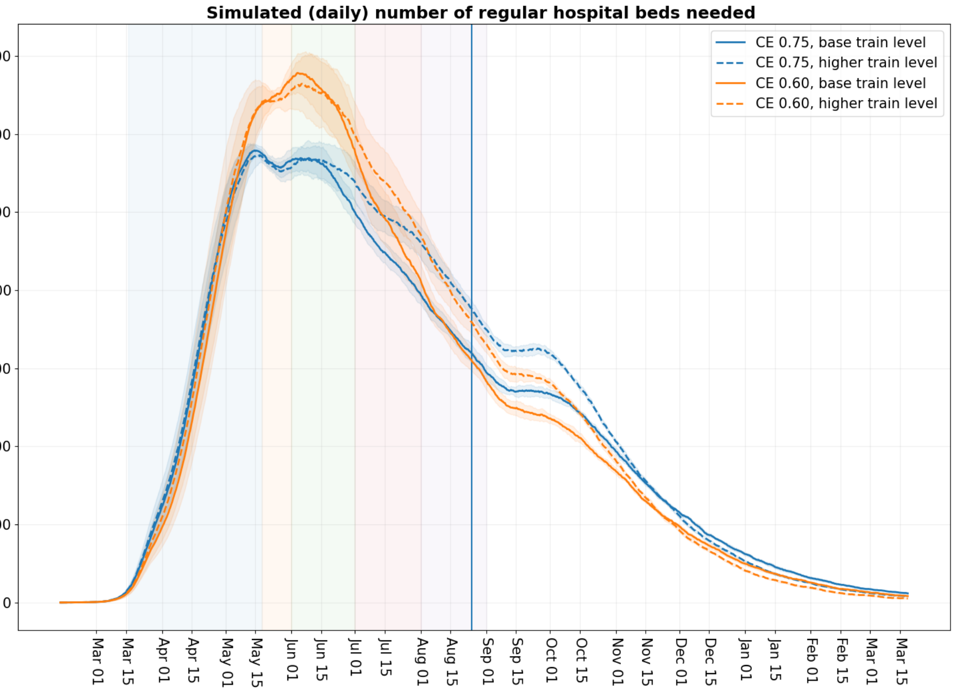
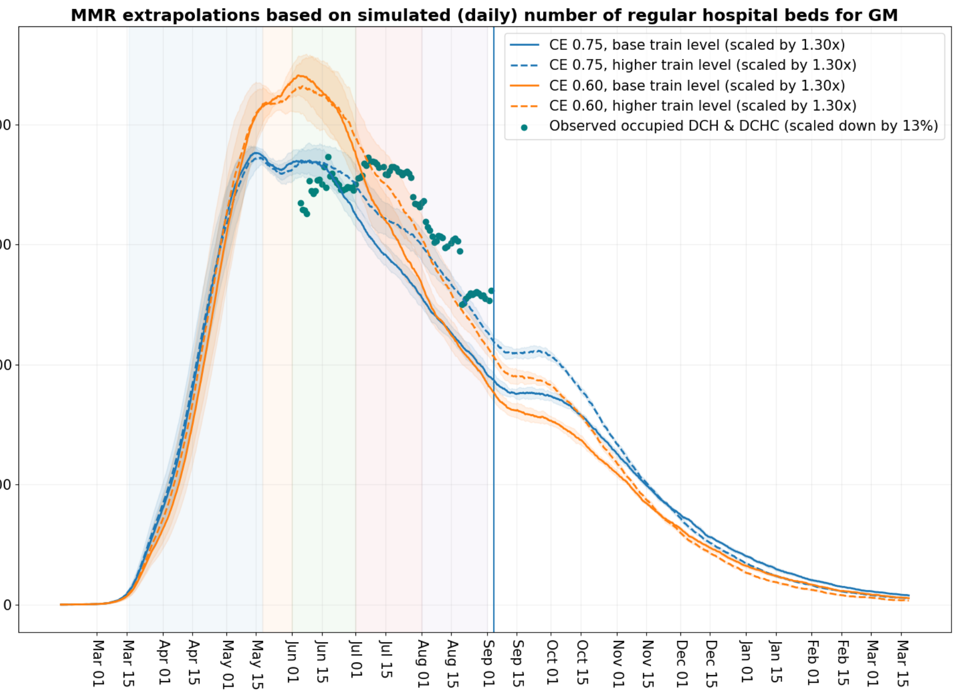


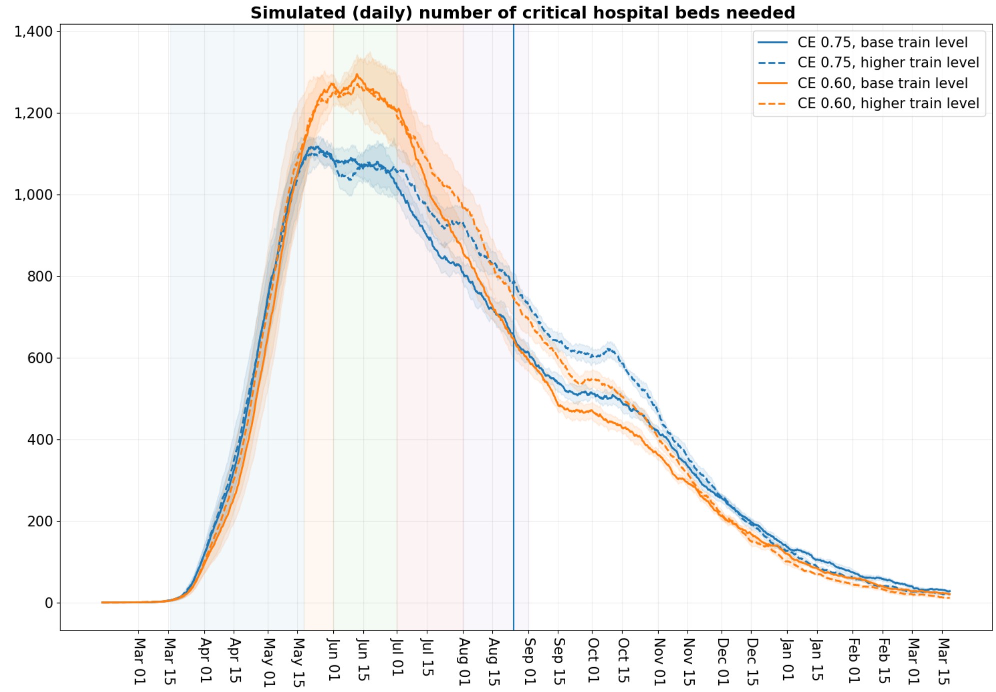
Figure 4: Simulated prevalence in Mumbai slums (HD areas) and non-slums under the workplace opening schedule 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% September onwards. The herd immunity in slums is attained at around 75%, while in non-slums it is attained at prevalence close to 50%.



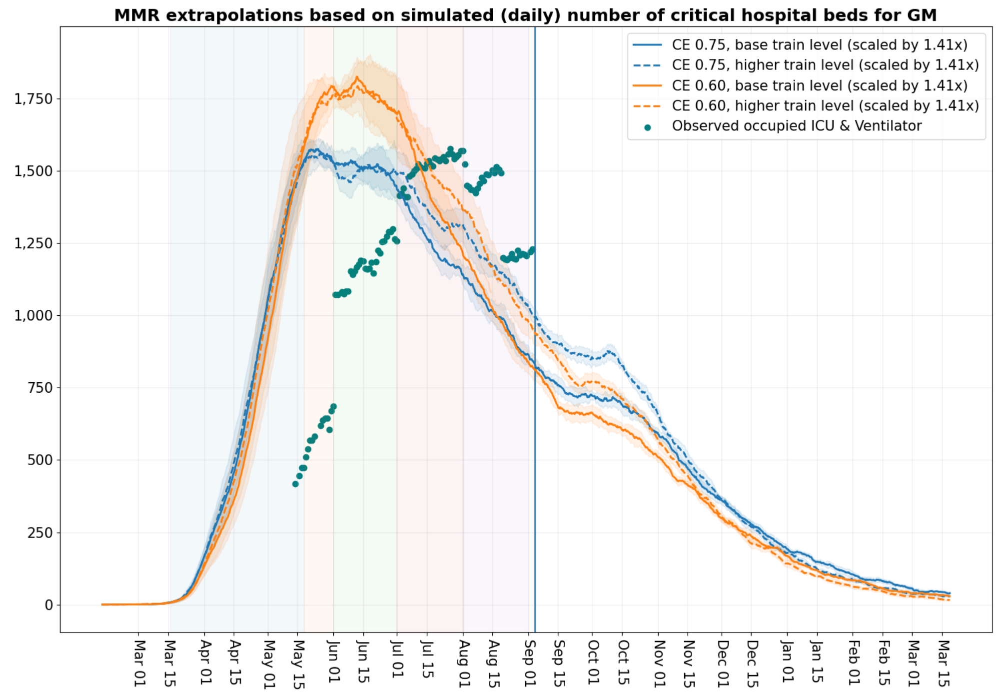
(a) Simulated daily hospitalised patients in the city under the workplace opening schedule 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% September onwards.



(b) Comparison of simulated daily hospitalised patients in the city with the DCH and DCHC numbers reported by BMC. The simulated numbers are increased by 30% to account for estimated patients coming from the other MMR areas. These cases came to Mumbai mainly in mid-July. The ICU numbers are removed from the reported DCH and DCHC numbers. These numbers are further reduced by 13% to remove the estimated asymptomatic patients in DCH and DCHC to facilitate comparison.

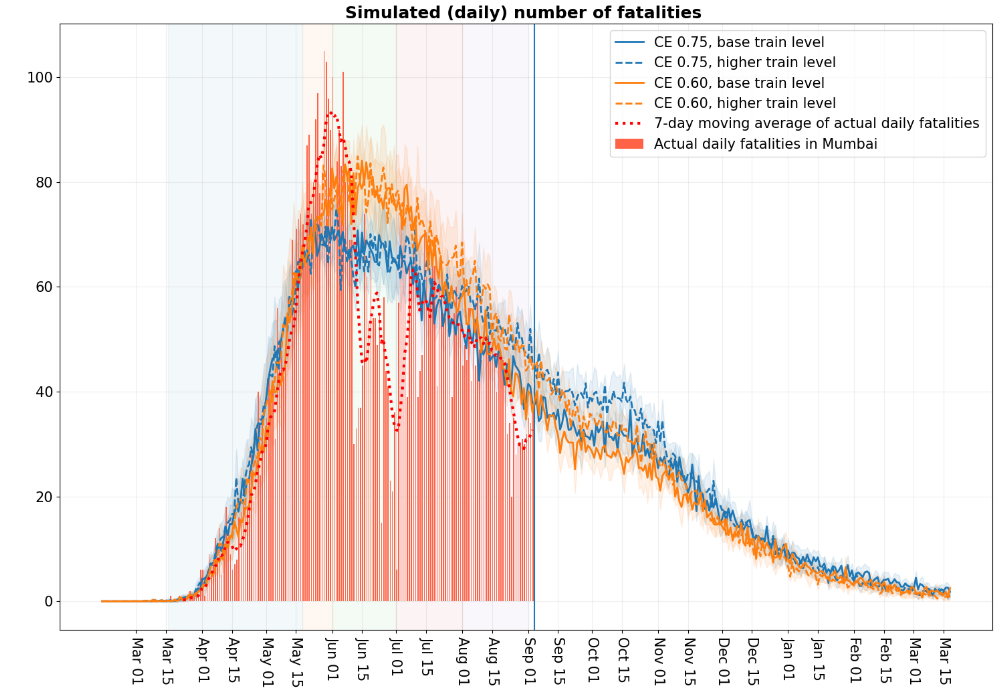


(a) Simulated daily critical patients in the city under the workplace opening schedule 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% September onwards.

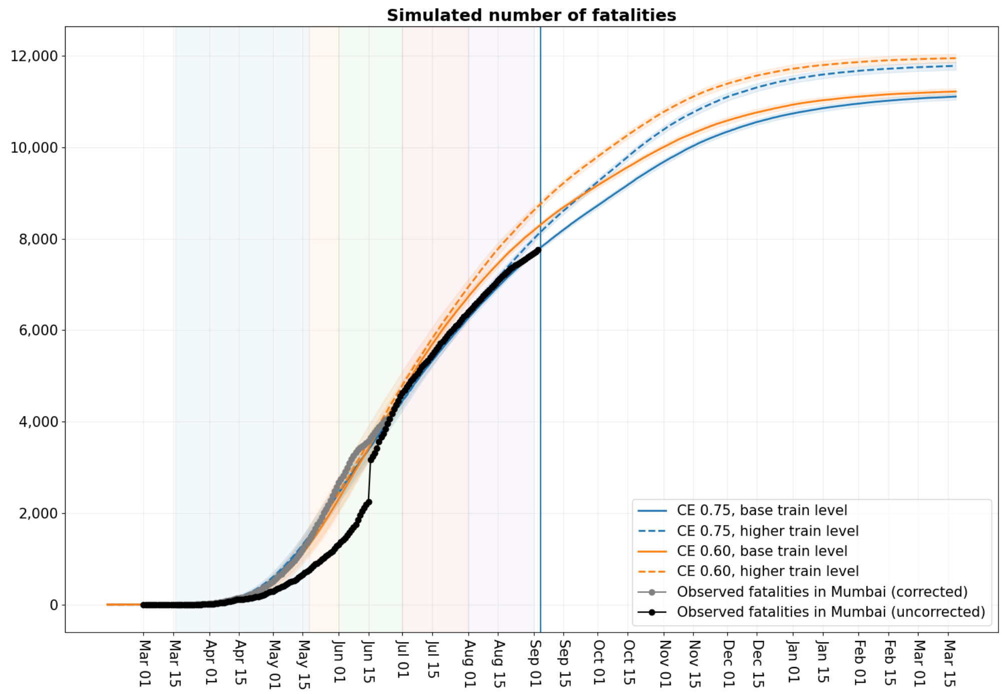


(b) Comparison of simulated daily critical patients in the city with the DCH and DCHC numbers reported by BMC. The simulated numbers increased by 41% to account for estimated patients coming from the other MMR areas. These cases came to Mumbai from around mid-July.

Figure 6

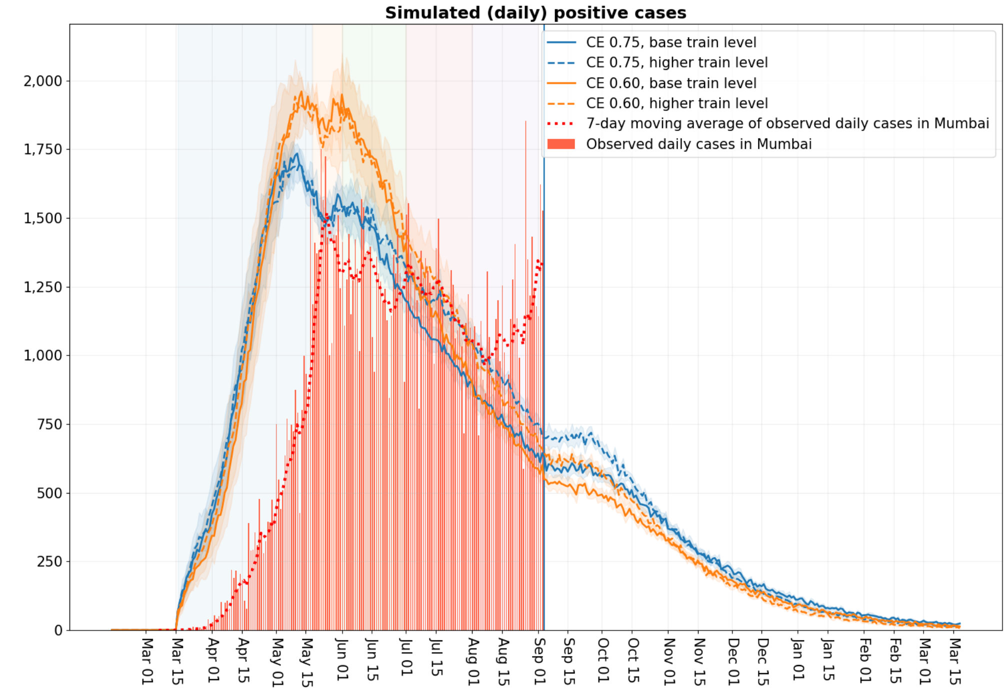


(a) Simulated daily deaths in the city under the workplace opening schedule 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% September onwards.

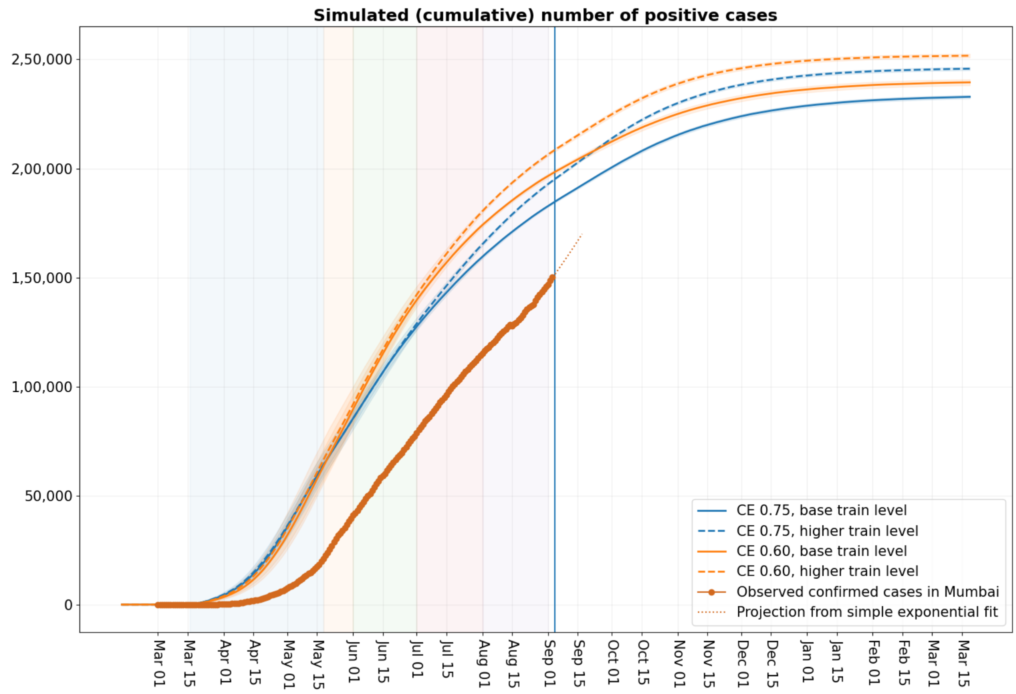


(b) Simulated cumulative fatalities in the city under the workplace opening schedule 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% September onwards. As per the simulations, the fatalities in the city stabilize around 12,000 by the end of the year.

Figure 7



(a) Simulated daily reported cases in the city under the workplace opening schedule 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% September onwards. While our algorithm with its rules designed to roughly reflect practice, matches the the observed recorded cases quite well from May 15 onwards till late August, it substantially overestimates the observed cases before May 15. This may be due to increase in testing in the city from around mid-May.



(b) Simulated cumulative reported cases in the city under the workplace opening schedule 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% September onwards.

Figure 8

V. Fully operational of economic activity

In Figure 9, we plot the simulated hospitalisations as well as critical cases where we overlay our base scenario with three separate ones

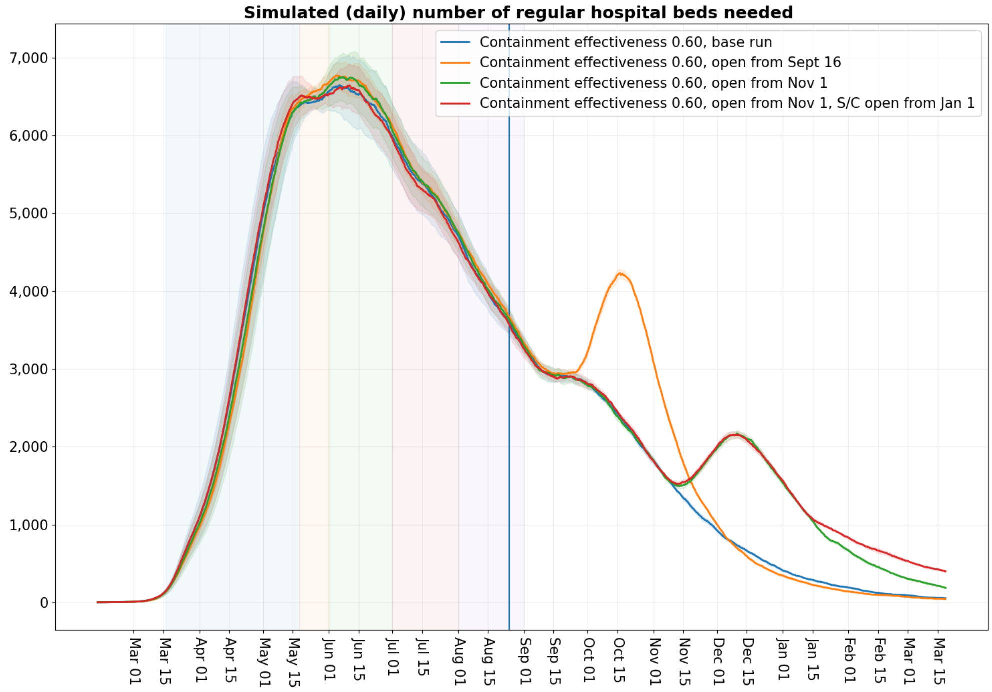
- Workplaces fully open on September 16.
- Workplaces fully open on November 1.
- Along with workplaces fully operational on November 1, schools and colleges reopening on January 1, 2021.

Our key observations are that the second wave of hospitalisations and critical cases is much higher with the September 16 th opening compared to the November 1 opening. While the projected hospitalisations increase from around 3,000 a day to a peak of about 4,200 a day with the September 16 opening, the increase is from about 1,600 a day to around 2,100 a day on November 1 opening. A much more manageable number from the medical infrastructure viewpoint.

Further, the opening of the schools on January 1 lead to only a small increase in hospitalisations and critical cases.

Figure 10 reflects a similar pattern in fatalities observed under these fully operational scenarios. While the projected daily fatalities increase from around 35 a day to a peak of about 50 a day with the September 16 opening, the increase is from about 18 a day to a peak of around 25 a day on November 1 opening.

Figures 11 and 12 show a similar pattern in reported cases and in number infected observed under these fully operational workplace scenarios.



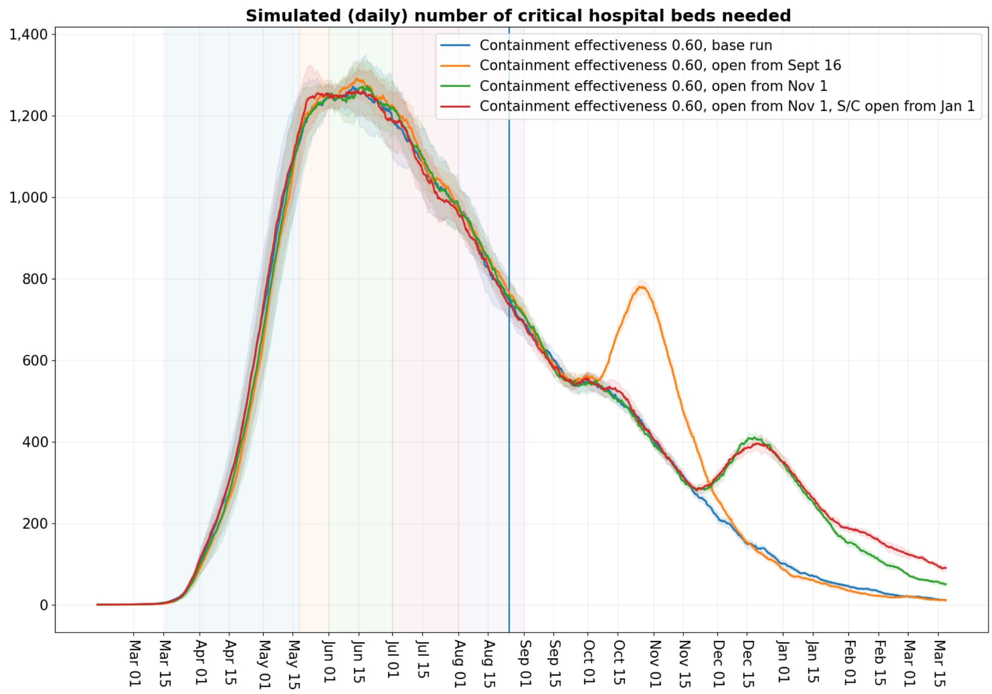
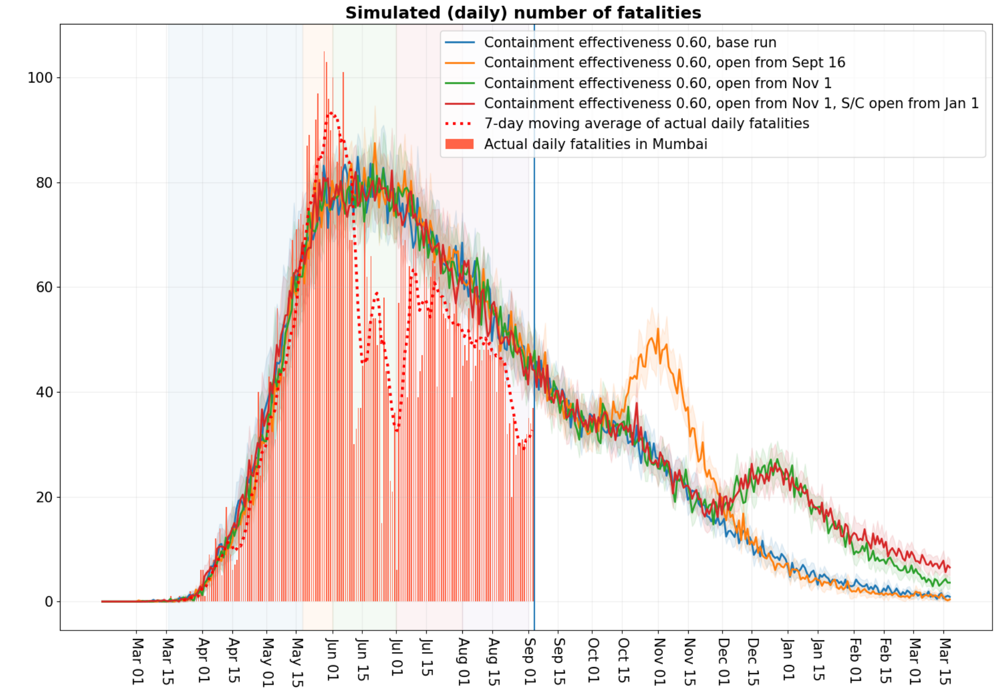


Figure 9: Simulated number of daily hospitalized patients and daily critical cases under the workplace opening schedule 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% in September. This schedule is overlaid with scenarios of workplace attendance of 100% from September 16, workplace attendance of 100% from November 1, and workplace attendance of 100% from November 1 with schools and colleges opening from January 1, 2021. While the projected hospitalisations increase from around 3,000 a day to a peak of about 4,200 with the September 16 opening, the increase is from about 1,600 to 2,100 on November 1 opening.



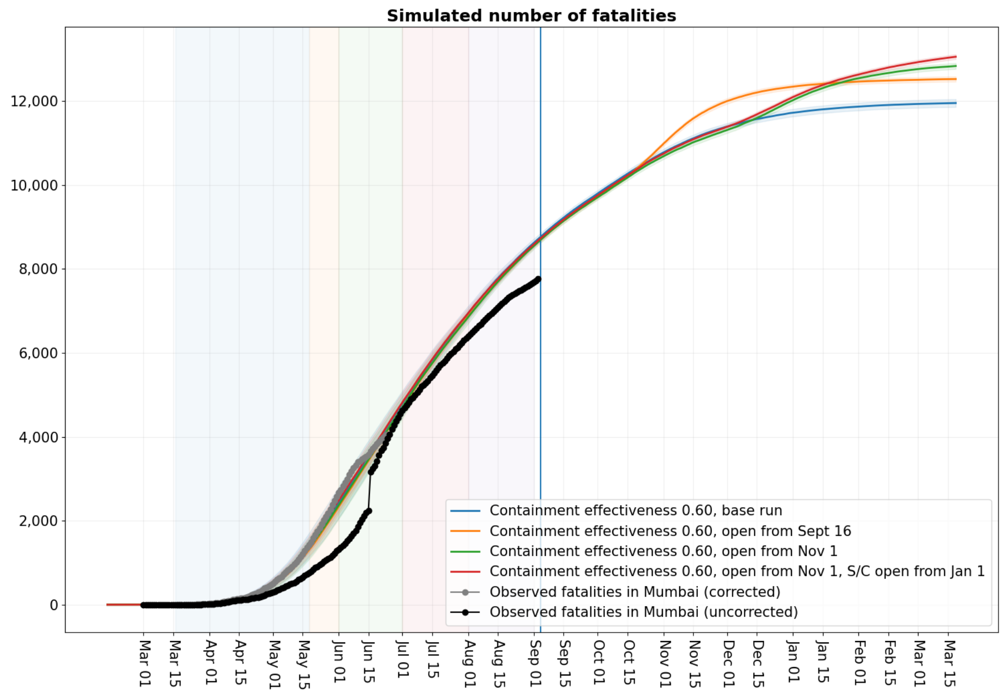


Figure 10: Simulated number of daily and cumulative fatalities under the workplace opening schedule 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% in September. This schedule is overlaid with scenarios of workplace attendance of 100% from September 16, workplace attendance of 100% from November 1, and workplace attendance of 100% from November 1 with schools and colleges opening from January 1, 2021. While the projected daily fatalities increase from around 35 a day to a peak of about 50 with the September 16 opening, the increase is from about 18 to 25 on November 1 opening.

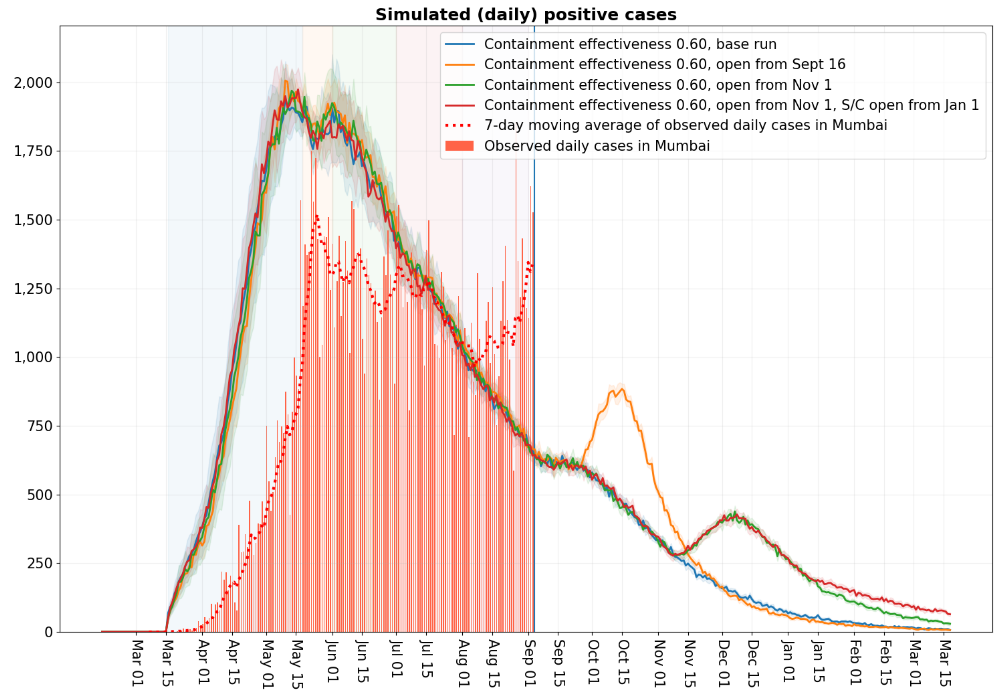
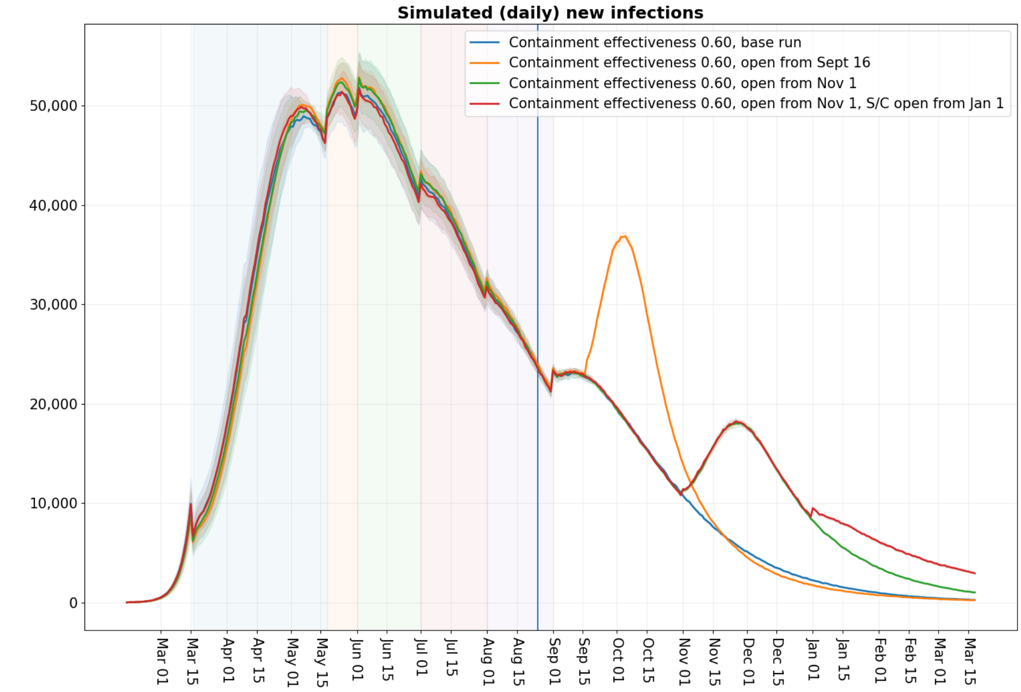


Figure 11: Simulated number of daily reported under the workplace opening schedule 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% in September. This schedule is overlaid with scenarios of workplace attendance of 100% from September 16, workplace attendance of 100% from November 1, and workplace attendance of 100% from November 1 with schools and colleges opening from January 1, 2021.



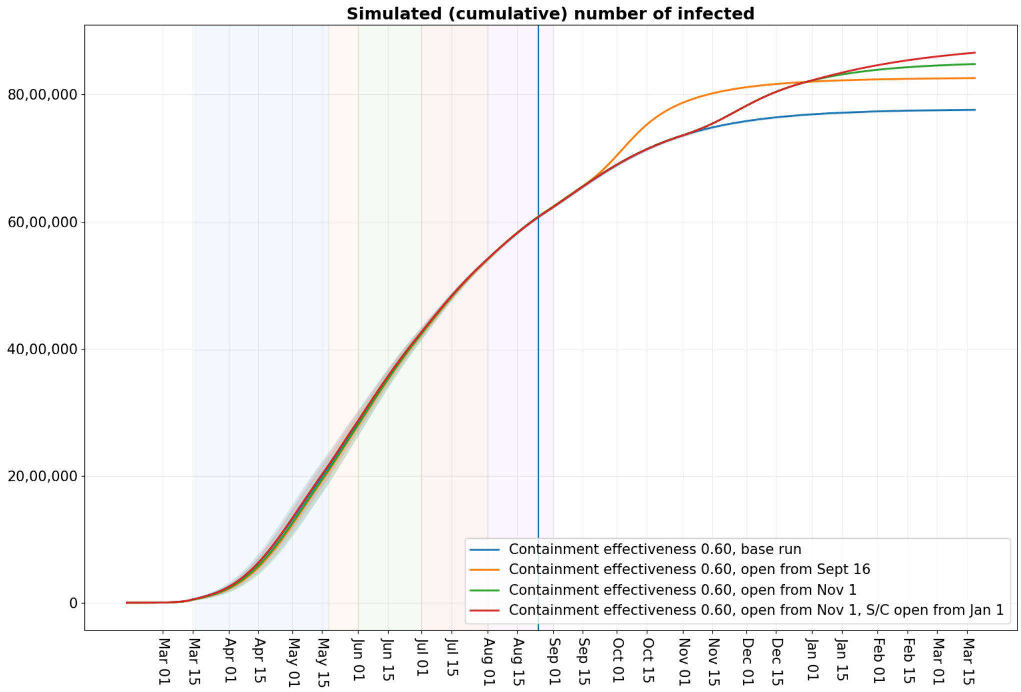


Figure 12: Simulated number of daily and cumulative reported under the workplace opening schedule 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% in September. This schedule is overlaid with scenarios of workplace attendance of 100% from September 16, workplace attendance of 100% from November 1, and workplace attendance of 100% from November 1 with schools and colleges opening from January 1, 2021.

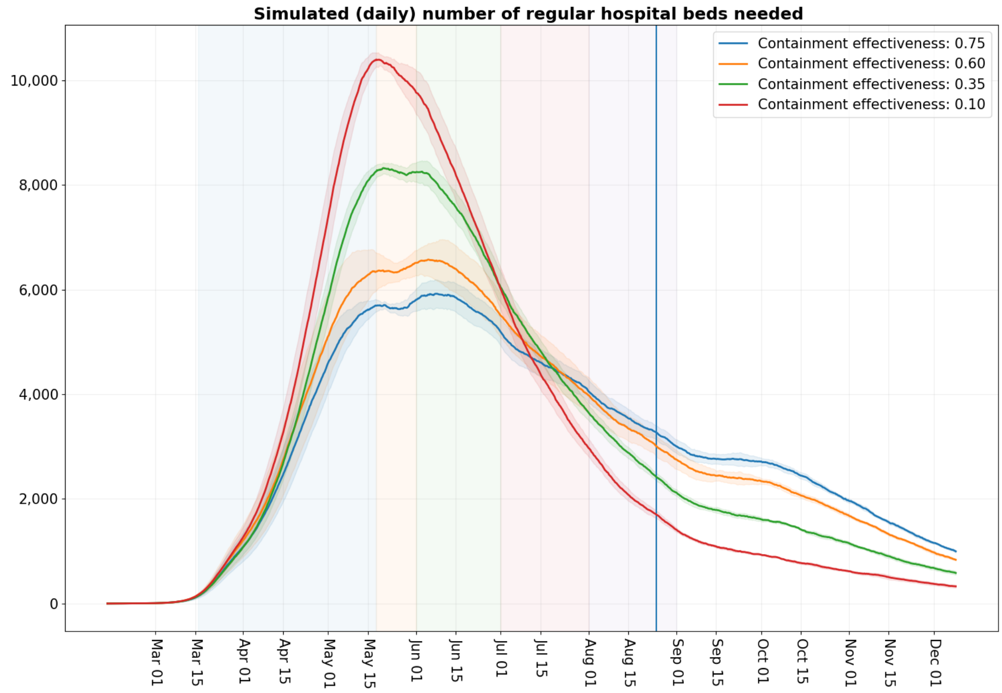
VI. Comparing containment zones with contact tracing and testing

Figures 13 and 14 show the impact of increasing containment effort on the resulting city medical statistics. Recall that containment efforts reduce the movement of individuals within the neighbourhood containment cell as well as those going out from or coming into the containment cell. The graphs indicate that containment efforts go a long way in slowing the infection. Thus, containment is an effective tool available to policy makers for slowing down the infection spread.

Figures 15 and 16 show the impact of increasing contact tracing and testing on the resulting city medical statistics. To test the intensity of contact tracing and testing, we consider three scenarios where the hospital index probability (the probability with which a hospitalised case is tested) takes values 0.66, 0.80 and 1.0.

The conclusion is that while contact tracing and testing does help in slowing the spread of the infection, the amount of reduction appears much less compared to that achieved through containment efforts, particularly since the latter appears to be cheaper and easier to implement.

The comparison between benefits of containment vis-a-vis contact tracing and testing is crystallised in Figure 17 where we plot the peak of moving ten day average of daily hospitalised patients as a function of these efforts. The contact tracing and testing effort measured on the x axis of the right hand figure corresponds to the hospital index probability for values 0.66, 0.80 and 1.0. We also consider the two higher contact tracing and testing cases where the hospital index probability is kept fixed at 1 but the remaining testing probabilities in the protocol are increased by 25% in one case and 50% in the other. These cases correspond to x-axis values of 1.25 and 1.5 in Figure 17.



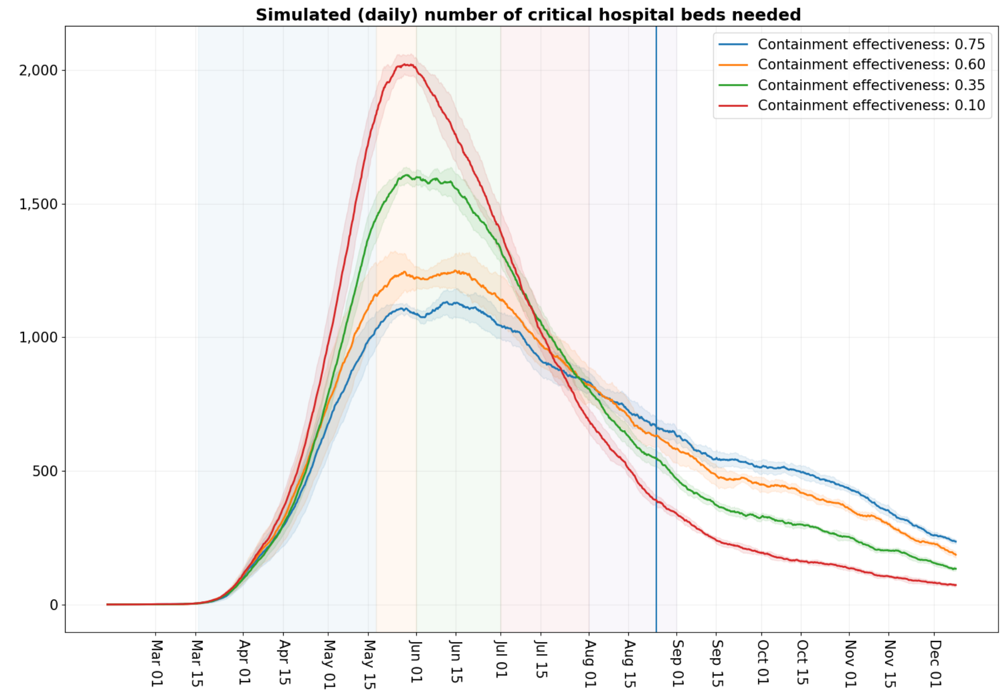
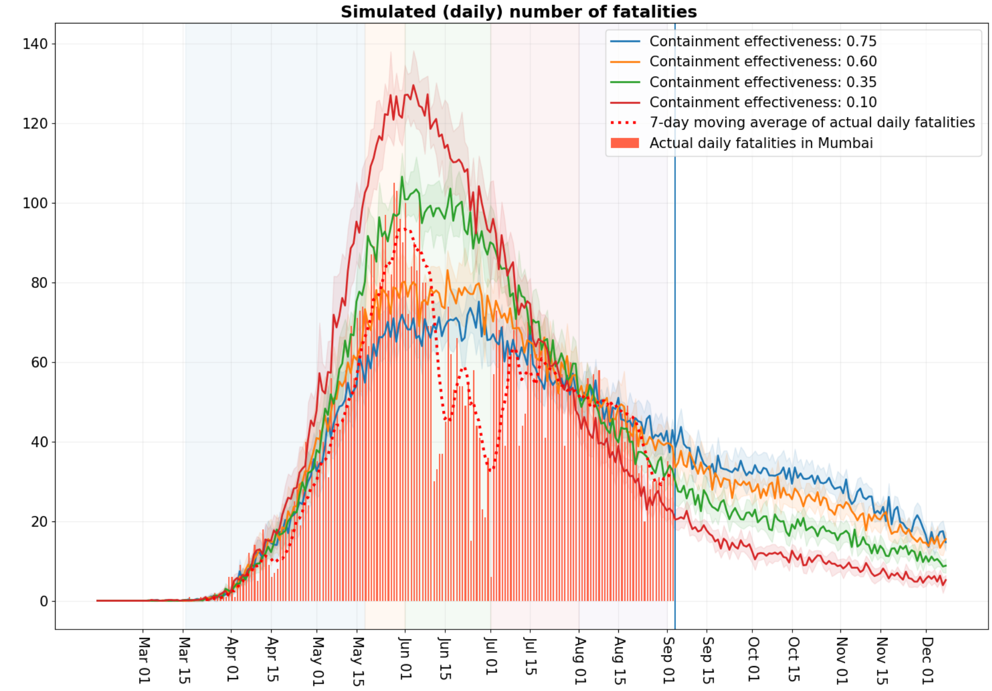


Figure 13: Simulated number of daily hospitalised patients and critical patients under varying level of containment efforts. Workplace opening schedule is set at 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% in September. The train transmission parameter β_T is set to its higher value $0.3 * \beta_H$.



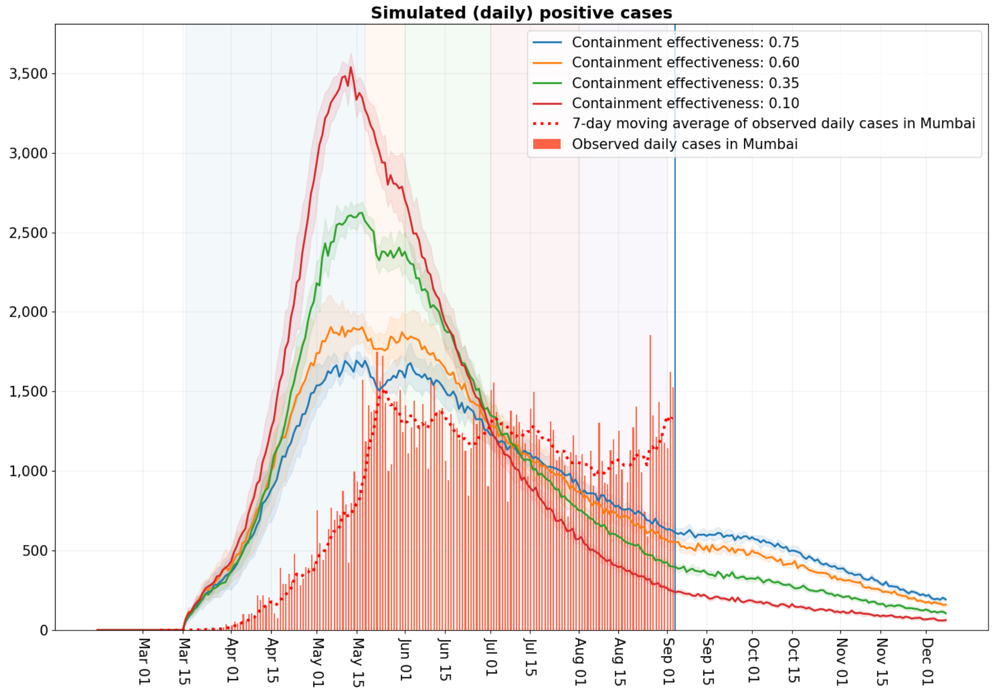


Figure 14: Simulated number of daily fatalities and daily recorded cases under varying level of containment efforts. Workplace opening schedule is set at 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% in September. The train transmission parameter β_T is set to its higher value $0.3 * \beta_H$.

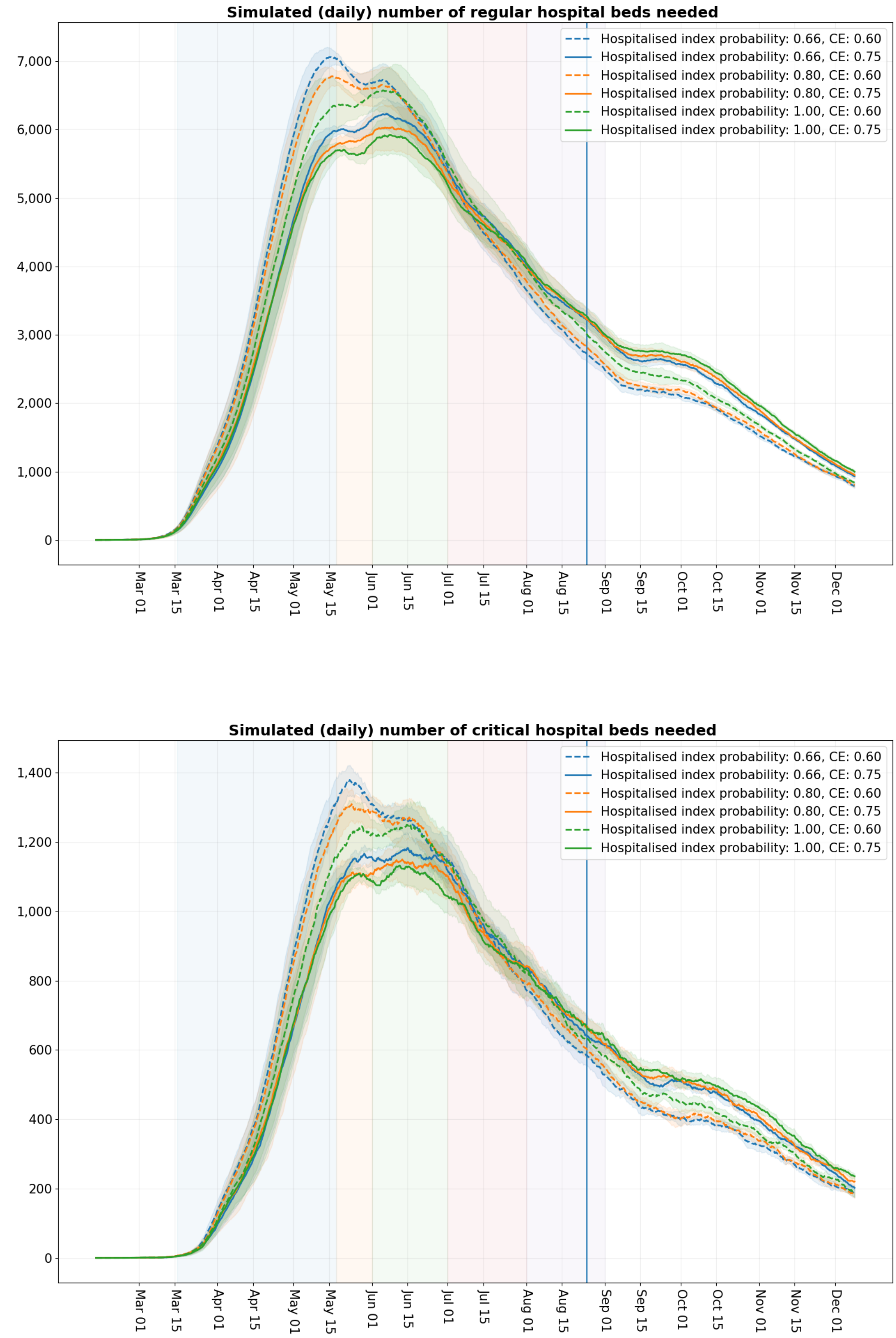
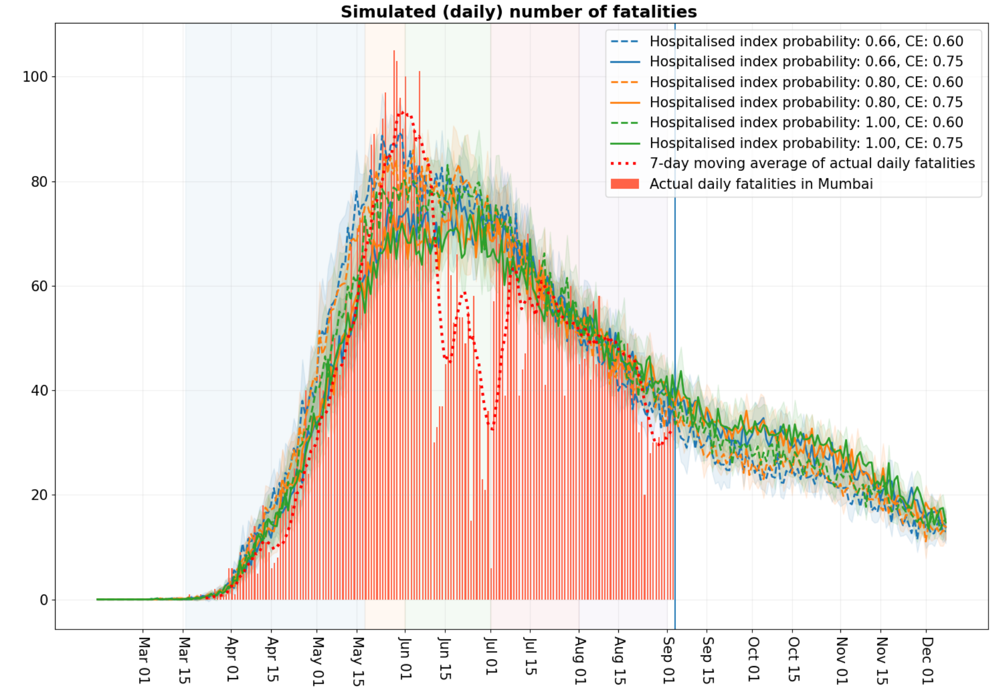


Figure 15: Simulated number of daily hospitalised patients and critical patients under varying level of contact tracing and testing strategies. Workplace opening schedule is set at 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% in September. The train transmission parameter β_T is set to its higher value $0.3 * \beta_H$.



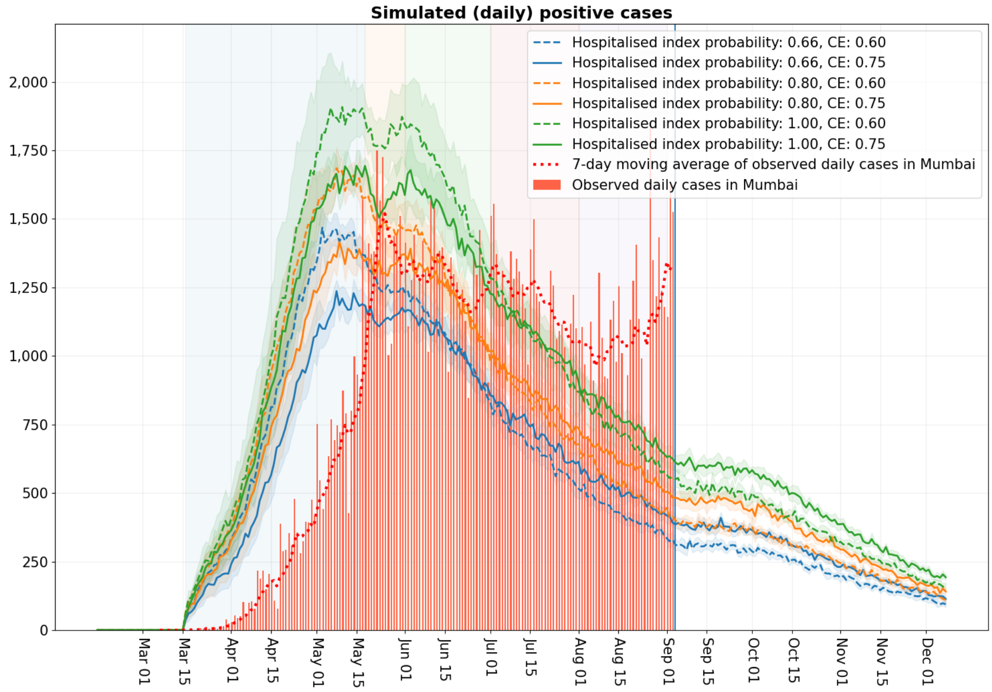


Figure 16: Simulated number of daily fatalities and daily reported cases under varying level of contact tracing and testing strategies. Workplace opening schedule is set at 5% attendance, May 18 to May 31st, 15% attendance in June, 25% in July, 33% in August and 50% in September. The train transmission parameter β_T is set to its higher value $0.3 * \beta_H$.

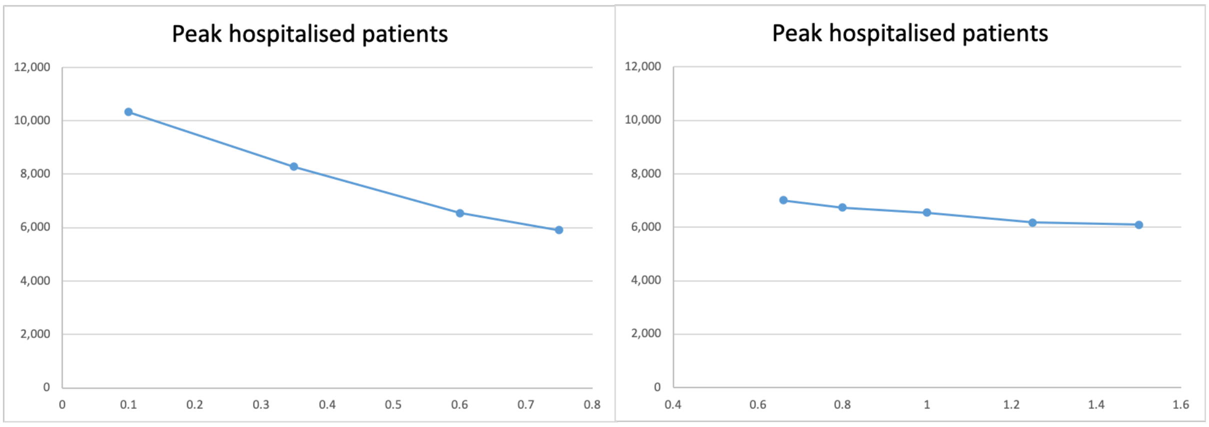


Figure 17: Comparison between benefits of containment effort vis-a-vis contact tracing and testing. The left figure reports the peak of moving ten day average of daily hospitalised patients as a function of containment effort. The right figure reports the same peak as a function of contact tracing and testing efforts.

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