Evaluating COVID-19 Lockdown Policies For India: A Preliminary Modeling Assessment for Individual States

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ABSTRACT

Background: On March 24, India ordered a 3-week nationwide lockdown in an effort to control the spread of COVID-19. While the lockdown has been effective, our model suggests that completely ending the lockdown after three weeks could have considerable adverse public health ramifications. We extend our individual-level model for COVID-19 transmission [18] to study the disease dynamics in India at the state level for Maharashtra and Uttar Pradesh to estimate the effect of further lockdown policies in each region. Specifically, we test policies which alternate between total lockdown and simple physical distancing to find "middle ground" policies that can provide social and economic relief as well as salutary population-level health effects.

Methods: We use an agent-based SEIR model that uses population-specific age distribution, household structure, contact patterns, and comorbidity rates to perform tailored simulations for each region. The model is first calibrated to each region using publicly available COVID-19 death data, then implemented to simulate a range of policies. We also compute the basic reproduction number R_0 and case documentation rate for both regions.

Results: After the initial lockdown, our simulations demonstrate that even policies that enforce physical distancing while otherwise returning to normal activity could lead to widespread outbreaks in both states. However, "middle ground" policies that alternate weekly between total lockdown and physical distancing may lead to much lower rates of infection while simultaneously permitting some return to normalcy.

KEYWORDS

COVID-19, India, modeling, Agent-based model, physical distancing, lockdown

1 INTRODUCTION

As of April 12, 2020, SARS-CoV2 – the pathogen responsible for COVID-19 – has resulted in an estimated 1.8 million reported cases and an estimated 113,000 reported deaths worldwide [1]. In the absence of effective interventions, India's population in particular is poised to suffer serious public health ramifications from the spread of COVID-19 due to its densely populated cities and relatively low critical care capacity [12, 14]. Accordingly, on March 24, 2020, India ordered a 3-week nation-wide lockdown.

This paper focuses on policy choices facing India following this initial 3-week lockdown. We model the impact of potential policy interventions in Maharashtra and Uttar Pradesh, two of the states hit hardest by COVID-19. Other India-specific epidemiological models have been introduced to forecast cases [5] or test interventions such as quarantine or lockdown [6, 15]. Instead, this paper specifically evaluates a class of policies which alternate between periods of complete lockdown and periods of physical distancing. During physical distancing, policies are put in place to limit contacts, but some amount of normal economic activity resumes. Such policies have been suggested before as a viable alternative to complete lockdowns, thus ameliorating some of the social and economic burden associated with the latter [4, 7, 16]. However, to our knowledge, there is no existing assessment of alternating these non-pharmaceutical interventions in the Indian context at the state level. India and its states have a number of distinctive characteristics that may impact the transmission of and fatality due to SARS-COV2, including multigenerational household structures, comorbidity patterns, environmental conditions (e.g., pollution), and high population density in urban areas, among others. We have previously developed an individual-level SEIR model for COVID-19 that accounts for the age distribution, household structure, contact patterns, and comorbidities of a specific population. Here, we parameterize this model using demographic data for Maharastra and Uttar Pradesh and infer state-specific plausible ranges for the transmissibility and fatality of the disease – finding evidence for substantial between-state variation. Using these estimates, we evaluate the success of "middle ground" policies – namely, those that alternate lockdowns with periods of physical distancing – at controlling the epidemic after the initial lockdown is lifted. Our results indicate that such "middle ground" policies are a viable option that may be able to limit the spread of COVID-19 in India while reducing the substantial costs of a full lockdown. However, relying entirely on milder physical distancing policies (i.e., discontinuing lockdowns entirely) may lead to rapid growth in infections and deaths. Until alternative interventions become available, occasional periods of intensive restriction may be necessary in India on an ongoing basis.

2 RESULTS

The SEIR model, described in Figure 1, tracks the number of susceptible, exposed, infected, removed (i.e., recovered or deceased) each day in the simulation. To fit the the model to a new region, we calibrate the model's internal parameters such that the number of COVID-19-related deaths produced by the simulation match what has been reported over the time period for which data are available. For more details, as well as estimations of R_0 and the infection documentation rate for each state, please see the appendix. For fitting, daily data on reported deaths and reported cases for both regions were collected from Indian governmental websites [3, 11] or news sources if time series data were otherwise unavailable [8, 9, 17]. Remaining data sources were collected at either the state-level or country-level as noted in Table 1. For more details about the model please see [18].

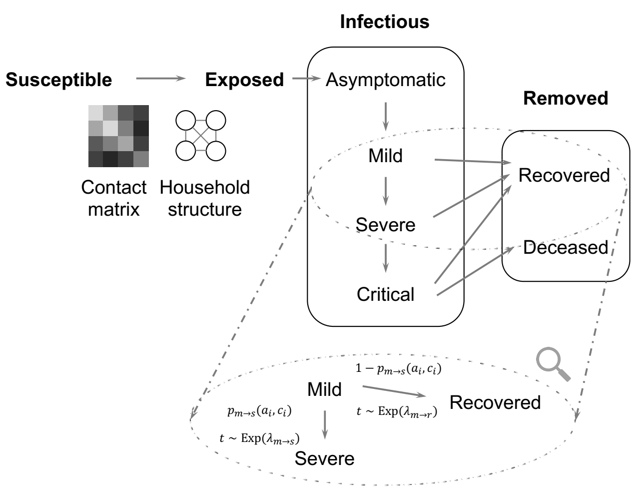

Figure 1: We use a modified SEIR model, where the infectious states are subdivided into levels of disease severity. The transitions are probabilistic, and there is a time lag for transitioning between states. For example, the magnified section shows the details of transitions between mild, recovered, and severe states. Each arrow consists of the probability of transition (e.g., $p_{m\to s}(a_i, c_i)$ to progress from mild to severe) as well as the associated time lag for the transition (e.g. the time t to progress from mild to severe is drawn from an exponential distribution with mean $\lambda_{m\to s}$). a_i and c_i denote the age and set of comorbidities of the infected individual i.

2.1 Various levels of physical distancing

Various interventions – from complete lockdown to physical distancing recommendations – have been implemented worldwide in response to COVID-19. Within these are a range of alternatives. For example, a government could impose various levels of physical distancing at different points in time, or encourage some percentage of a given age group to remain sheltered in place, while the rest of the population could continue in-person work and social activities.

The policy interventions simulated over a seven-week horizon (i.e., April 14 - June 7) are a combination of two non-pharmaceutical interventions (NPIs), "L"and "S". Both aim to reduce the average number of contacts any given individual has on a daily basis. "L" represents a scenario of a full population lockdown, and can be interpreted as a reduction by a factor of 30 of social interactions on a daily basis, whereas "S"–which can be thought of as a less stringent physical distancing measure–corresponds to a reduction by a factor of 2. In practical terms, and in light of the age-stratified contact matrix estimated for India across locations (i.e., home, work, school, etc.) [13], the real-world implications for the three generations that compose the working age populations, in terms of social behavior change, would be as follow:

- For individuals aged 15–29: switch from an average of 76–87 daily contacts to an average of 38–43 or 0.9–2.6 daily contacts, under "S" and "L" scenarios respectively.
- For individuals aged 30–49: switch from an average of 47–49 daily contacts to an average of 23–25 or 1–2 daily contacts, under "S" and "L" scenarios respectively.
- For individuals aged 50–69: switch from an average of 11–27 daily contacts to an average of 5–14 or 0–1 daily contacts, under "S" and "L" scenarios respectively.

For both the states of Maharashtra and Uttar Pradesh, we simulate the trajectory of the epidemics from just before the date at which the first case was reported (March 3 and 10, in Maharashtra and Uttar Pradesh, respectively), until June 7. Each policy scenario is composed of four successive interventions, the initial three lasting a week each and the last extending till the end of the simulation. At each decision time point, respectively on April 14, 21, 30, and on May 7, the policy can be either (1) maintained for at least another week or (2) replaced by a more stringent (i.e., transition from "S" to "L"), or less stringent policy (i.e., transition from "L" to "S"). The two most extreme scenarios reflect the maintenance of a single non-pharmaceutical intervention for at least seven contiguous weeks without any interruption: on the one hand, "SSSS" represents a mild physical distancing scenario (i.e., reduction of daily contacts by a factor of 2) for a total duration of seven weeks, while "LLLL" reflects a more drastic measure (i.e., reduction of daily contacts by a factor of 30).

We evaluate these policy interventions in two Indian states according to two distinct metrics: the total number of deaths (left panel), and the total number of infections (right panel) in Figures 2 and 3. Each colored line shows the impact of a given sequence of measures over time. The blue line represents the most lenient scenario, consistent with mild physical distancing for a period of seven weeks, while the pink line represents the most severe measure–a prolonged lockdown of the whole population for a period of seven weeks.

From our simulation-based analysis, strategies that would rely entirely on milder physical distancing policies, and thus completely discontinue lockdowns for weeks at a time, would likely be insufficient in curbing epidemics at the state level.

Table 1: Demographic and comorbidity data sources.

Type	Level	Source	Citation
Age Specific Fertility of Mothers	National	UN Population Division	[10]
Contact Matrices	National	Prem et al.	[13]
Age Distribution	State	USAID Demographic and Health Surveys	[2]
Household Type Distribution	State	USAID Demographic and Health Surveys	[2]
Diabetes Rates by Age	State	USAID Demographic and Health Surveys	[2]
Hypertension Rates by Age	State	USAID Demographic and Health Surveys	[2]

Building upon the case of Maharashtra and Uttar Pradesh, our model suggests that "middle ground" policies that alternate lockdown measures with physical distancing measures may be more effective at limiting final outbreak size than the most lenient SSSS policy. Such "middle ground" policies would also better allow for social and economic preservation than the most stringent LLLL policy. Our analysis can be readily extended to other locations in India by parameterizing our model for a new state population using existing demographic data and age-stratified contact patterns.

2.2 Alternating Policies for Maharashtra and Uttar Pradesh

We simulate a class of policies which alternate between complete lockdowns and milder physical distancing periods. Our simulation contains three time periods. First, from the start of the simulation until April 14 (the date for the end of the current national lockdown). Second, an “alternation period" where the policy alternates between complete lockdown (L) and physical distancing (S). This period continues until May 7. The alternation period allows us to look at the growth of the epidemic when milder restrictions are interspersed with lockdowns. Third, from May 7 until the end of the simulation, where only the policy which falls last in the alternating sequence is used. This period allows us to observe the impact of long-term use of a single policy (i.e., either lockdown or physical distancing).

In both states, we find that alternating policies result in fewer total simulated infections and deaths than the more lenient SSSS (i.e., physical distancing only) policy, while only performing marginally worse than the most stringent LLLL (i.e., lockdown only) policy (between the dashed lines in Figures 2 and 3). Note that a spike in simulated infections is only reflected among the simulated deaths after a short delay; because of this, we use the rate of new infections *during the alternating period* to evaluate the effectiveness of the policy. Additionally, policies that place lockdowns earlier in the alternation period appear to have a greater impact – indicating that early restrictions are more effective under an exponential growth paradigm. However, this effect is much stronger in Maharashtra since more cases were reported in Maharashtra (99 cases) than Uttar Pradesh (32 cases) [3], before the nationwide lockdown. This suggests that Maharashtra may need to extend the current lockdown longer than Uttar Pradesh before alternating policies.

Major differences in policy-mediated effects also arise after the alternation period ends (i.e., after the last dashed line), a period that extends from May 7 through June 7. Noticeably, policies that terminate in "S" (i.e., physical distancing) always result in a steep rise in both infections and deaths, as compared to policies that end with "L" (i.e., lockdown). This suggests that physical distancing can be effective when combined with periodic lockdowns to interrupt transmission, but that it cannot on its own curb either state-level epidemic.

3 CONCLUSION

We simulate various "middle ground" policies that alternate lockdowns with physical distancing for two Indian states. Our simulations suggest that such "middle ground" policies could provide an effective means to curb the otherwise exponential rates of infection and death while simultaneously allowing occasional social and economic reprieve. However, states that reported a greater number of cases before the nationwide lockdown may benefit from an extended period of lockdown before engaging in alternating policies.

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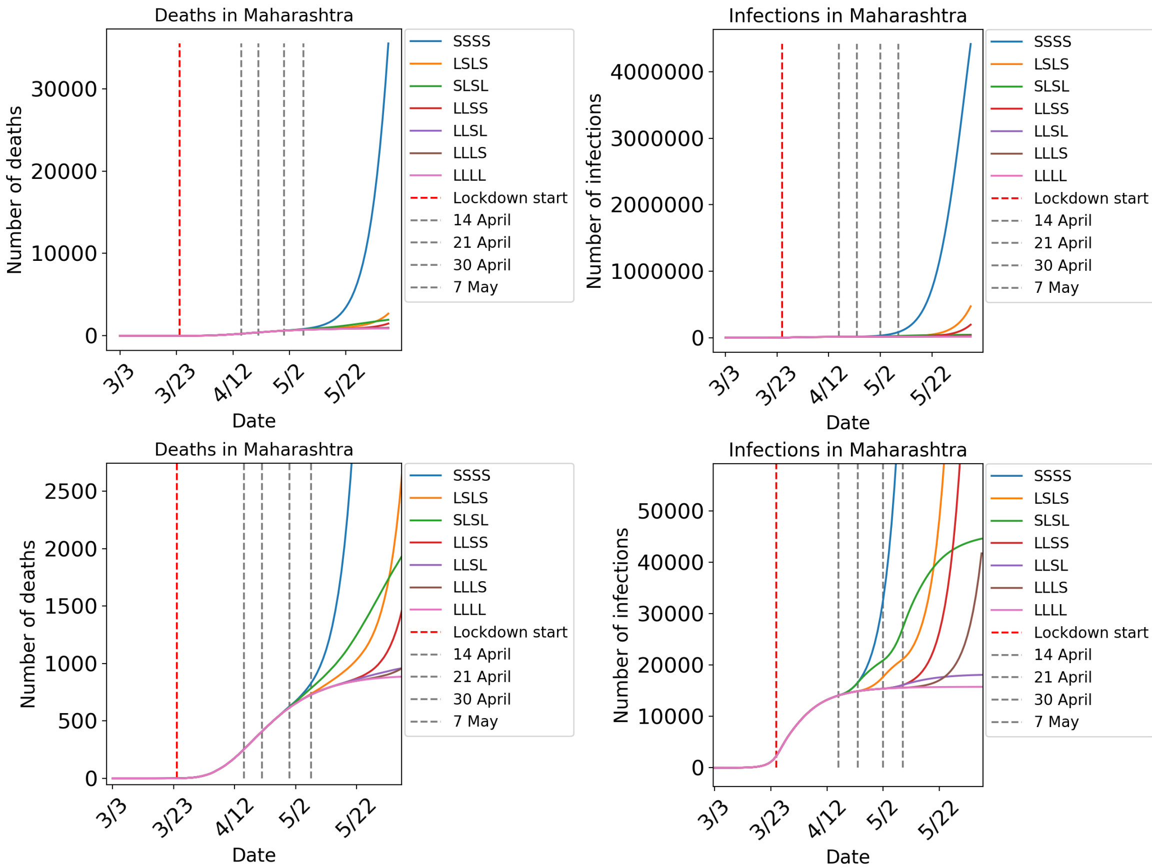

Figure 2: Comparative effectiveness of non-pharmaceutical interventions in the state of Maharashtra: this graph illustrates the effect of strategies alternating milder physical distancing policies (i.e., "S" time periods) with strict lockdown of the full population (i.e., "L" time periods) in Maharashtra state on the total number of simulated deaths (left panel) and infections (right panel). The overall trajectories are represented in the top row, while a zoomed-in version is provided in the bottom row. The red vertical dashed line indicates the start of the Indian national lockdown on March 24, 2020. Each of the four gray dashed lines represents a time point at which a policy change might occur. Each solid colored curve, obtained by averaging over 50 independent runs of the simulation, represents a specific sequence of measures, composed of "S" and "L" time periods, with each intervention sustained for at least one week. The following set of epidemic parameters was used for the state of Maharashtra: ($p_{\text{inf}} = 0.036$, t_0 = March 3, $d_{\text{mult}} = 4$).

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APPENDIX

A MODEL FITTING

The three parameters which must be tuned are: (1) p_{inf}, the probability of transmission given contact between an infected and susceptible individual; (2) t_0, "day zero" of the infection, which is not exactly known in most regions but must be tuned since it exerts a large impact due to rapid doubling times; (3) d_{mult}, which addresses remaining differences in the rate of mortality between locations of interest that are *not* captured by demographic factors in the model (e.g., the impact of greater pollution rates or availability of hospital beds). As in [18], $d_{\text{mult}} = 1$ corresponds to the COVID-19 mortality rate in Wuhan, China since the model's age- and comorbidity-specific COVID-19 mortality rates were calibrated using data from that region. For both Maharashtra and Uttar Pradesh, we show simulated death trajectories for one of many well-fitting sets of the above parameters.

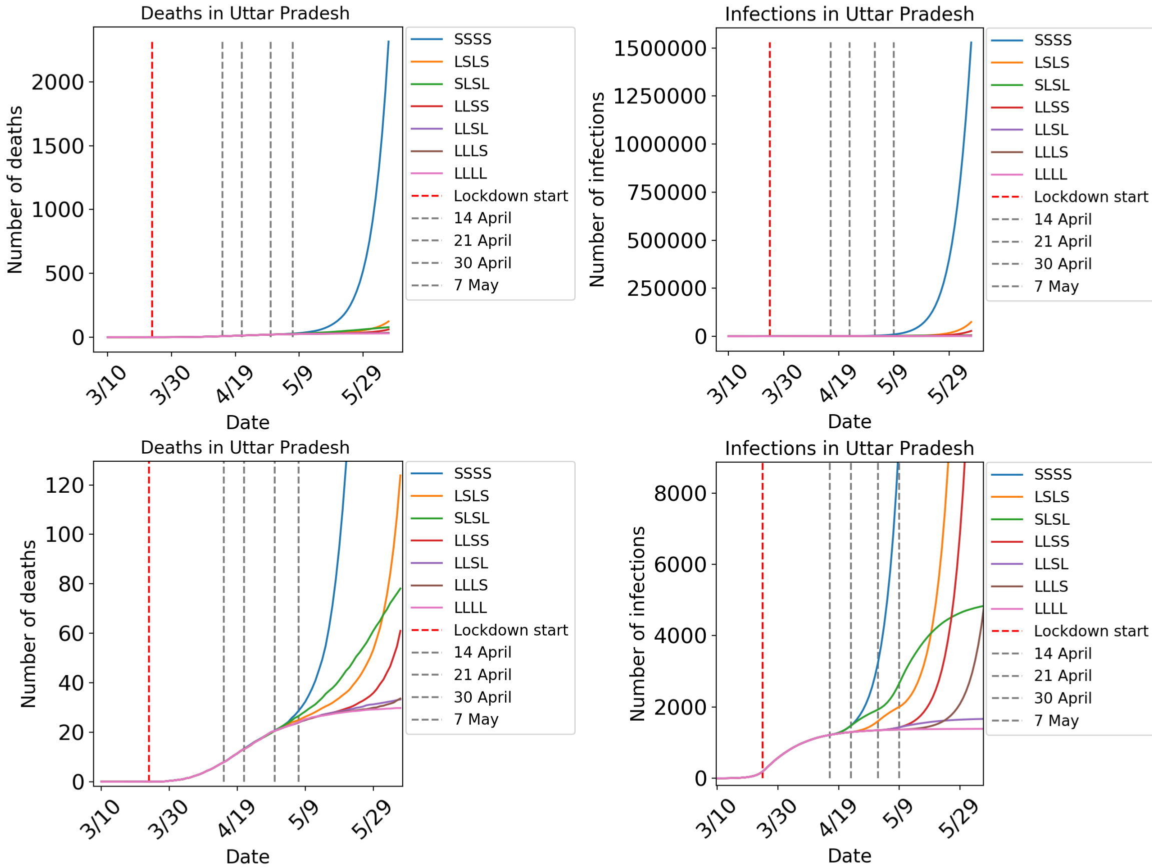

Figure 3: Comparative effectiveness of non-pharmaceutical interventions in the state of Uttar Pradesh: this graph illustrates the effect of strategies alternating milder physical distancing policies (i.e., "S" time periods) with strict lockdown of the full population (i.e., "L" time periods) in Uttar Pradesh state on the total number of simulated deaths (left panel) and infections (right panel). The overall trajectories are represented in the top row, while a zoomed-in version is provided in the bottom row. The red vertical dashed line indicates the start of the Indian national lockdown on March 24, 2020. Each of the four gray dashed lines represents a time point at which a policy change might occur. Each solid colored curve, obtained by averaging over 50 independent runs of the simulation, represents a specific sequence of measures, composed of "S" and "L" time periods, with each intervention sustained for at least one week. The following set of epidemic parameters was used: ($p_{\mathbf{inf}} = 0.036$, t_0 = March 10, $d_{\mathbf{mult}} = 4$).

A.1 Maharashtra

For Maharashtra, we simulate from a starting time t_0 varied around March 8 for the first confirmed cases in the state [11] through April 10, with lockdown on March 24. While we fit using only the final total of deaths, Fig. 4 shows that our simulations closely match the entire trajectory. Results presented in this section use 100 independent runs of the simulation.

It is important to note that several parameter combinations fit the data well, as shown in the heatmaps of Figures 5 and 6, where darker cells represent a better fit between reported deaths and simulated deaths. Goodness of fit is measured by testing whether the reported death count is well-contained within the distribution of simulations. Specifically, if p is the percentile of the true number of reported deaths in the distribution of the simulation runs, the color of the cell reflects $p(1-p)$ – darker colors reflect higher values. A value of 0 means that the true number of reported deaths is either greater or smaller than all simulation runs, and a value of 0.25 (the maximum possible) means that the true number of reported deaths is exactly at the 50$^{\text{th}}$ percentile of the simulated distribution.

Figures 5 and 6 also show associated values for infection documentation rate and R_0, respectively. We calculate plausible ranges for both by computing the range of all values for parameter settings where the percentile p of the true number of reported deaths in the simulated distribution satisfies $p(1-p) \geq 0.2$. For documentation rate, the plausible range is 7.09%–39.45% and for R_0, the plausible range is 3.00-4.21. This suggests that the rate of spread in the state is high compared even to that of the hard-hit region, Lombardy, in which the model previously estimated R_0 of 2.50–3.37 [18]. Nevertheless, the model also estimates a higher infection documentation rate for Maharashtra than in Lombardy (i.e., 1.14%–6.68%) [18].

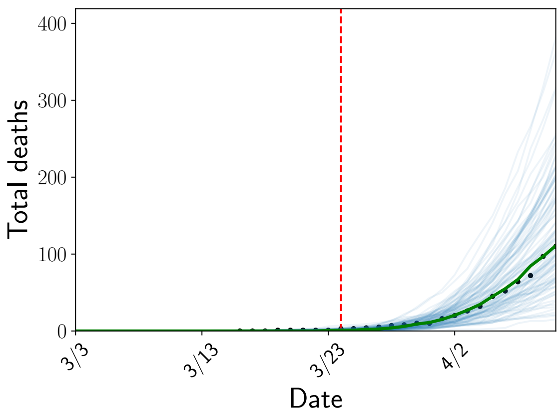

Figure 4: Simulated trajectories of deaths in Maharashtra (p_{inf} = 0.036, t_0 = March 3, d_{mult} = 4). Dotted black lines represent true reported COVID-19 deaths. Blue lines are independent simulations and the green line is the median of the simulations. The red dashed line marks the nationwide lockdown instated on March 24. The true number of reported deaths is well contained within the simulated trajectories and lies close to the median (Pearson $r = 0.997$)

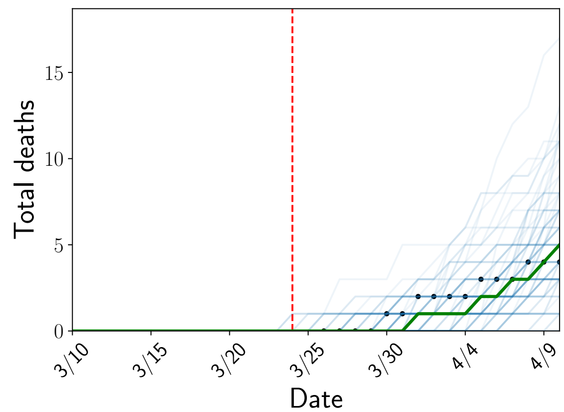

Figure 7: Simulated trajectories of deaths in Uttar Pradesh (p_{inf} = 0.036, t_0 = 10 March, d_{mult} = 6). Dotted black lines represent true reported COVID-19 deaths. Blue lines are independent simulations and the green line is the median of the simulations. The red dashed line marks the nationwide lockdown instated on March 24. The true number of reported deaths is well contained within the simulated trajectories and lies close to the median (Pearson $r = 0.917$)

A.2 Uttar Pradesh

For Uttar Pradesh, we simulate from a starting time t_0 varied around March 5 for the first confirmed cases in the state [8, 9, 17] through April 10, with lockdown on March 24. While we fit using only the final total of deaths, Figure 7 shows that our simulations closely match the entire trajectory. Results presented in this section use 100 independent runs of the simulation.

Figures 8 and 9 show associated values for infection documentation rate and R_0 respectively, in tandem with goodness of fit (where darker cells indicate a better fit). We calculate plausible ranges for both by computing the range of all values for parameter settings where the percentile p of the true number of reported deaths in the simulated distribution satisfies $p(1-p) \geq 0.2$. For documentation rate, the plausible range is 11.33%–99.54% and for R_0, the plausible range is 1.97–3.46. This suggests that the rate of transmission in the state may be lower than Maharashtra, but still comparable to hard-hit Lombardy (R_0 of 2.50–3.37 [18]). However, it is worth noting that the plausible range for both R_0 and documentation rate are large, likely due to the small number of confirmed deaths in the state, making fitting more challenging.

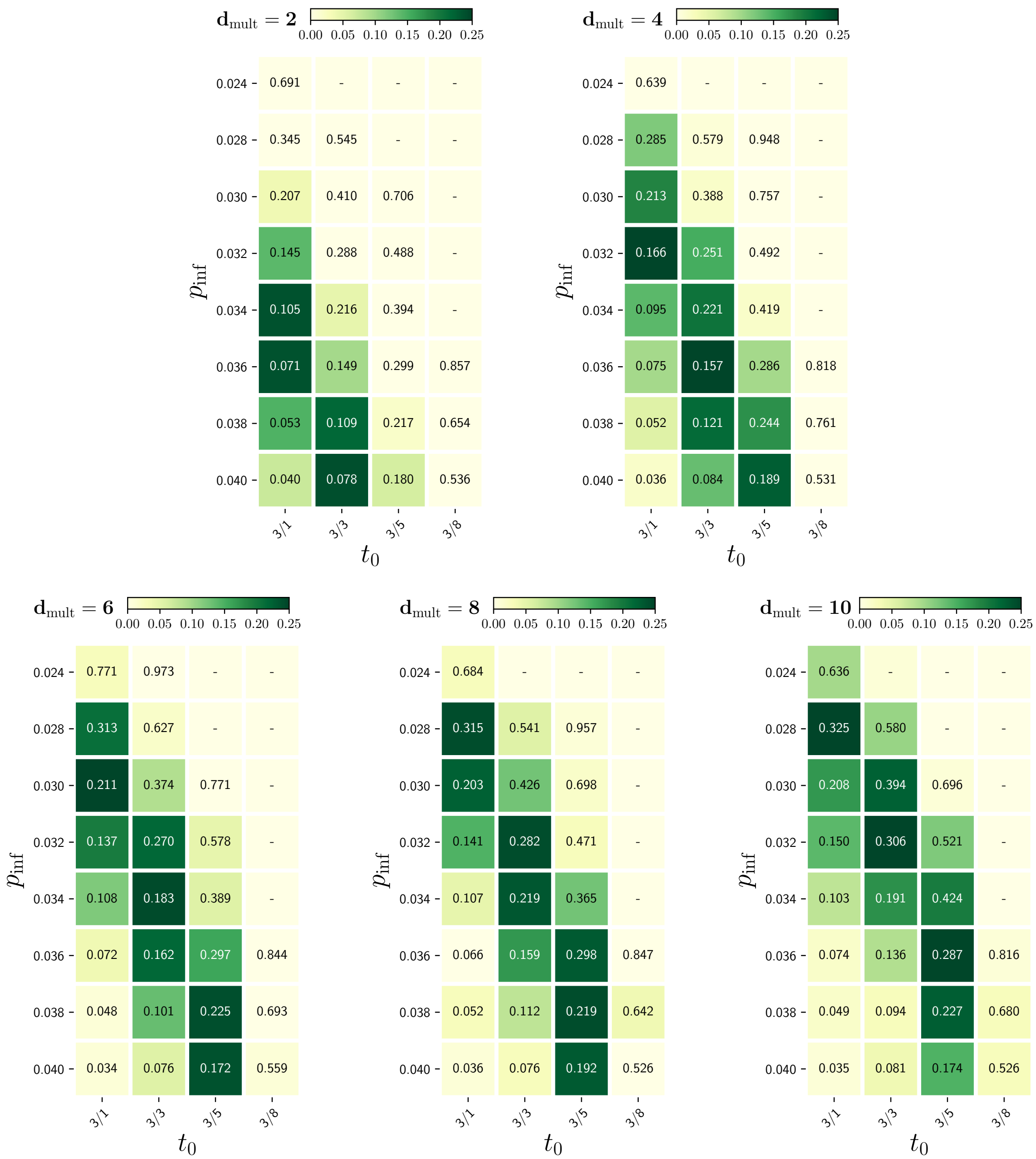

Figure 5: Estimated fraction of symptomatic infections that become documented in Maharashtra as a function of $p_{\mathbf{inf}}$ (y axis) and t_0 (x axis). Each plot corresponds to a higher mortality multiplier $d_{\mathbf{mult}}$. Darker cells indicate better goodness of fit of the corresponding parameter settings to the true number of reported deaths on April 10. A broad range of parameter combinations fit the data well, yielding a plausible range of 7.09%–39.45% for the documentation rate.

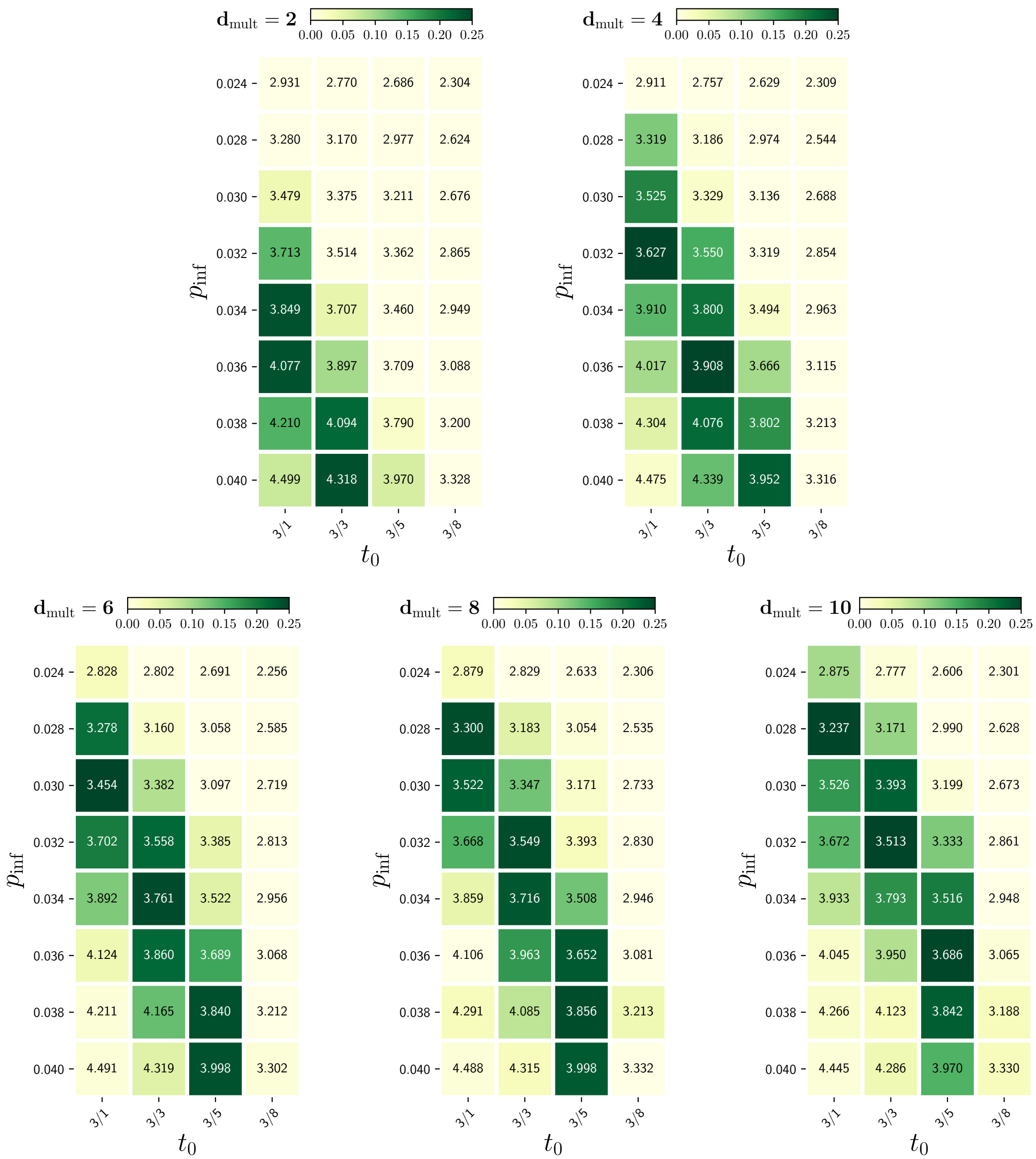

Figure 6: Estimated values of R_0 for Maharashtra during the pre-lockdown phase as a function of $p_{\mathbf{inf}}$ (y axis) and t_0 (x axis). Each plot corresponds to a higher mortality multiplier $d_{\mathbf{mult}}$. Darker cells indicate better goodness of fit of the corresponding parameter settings to the true number of reported deaths on April 10. A broad range of parameter combinations fit the data well, giving a plausible range of 3.00–4.21 for R_0.

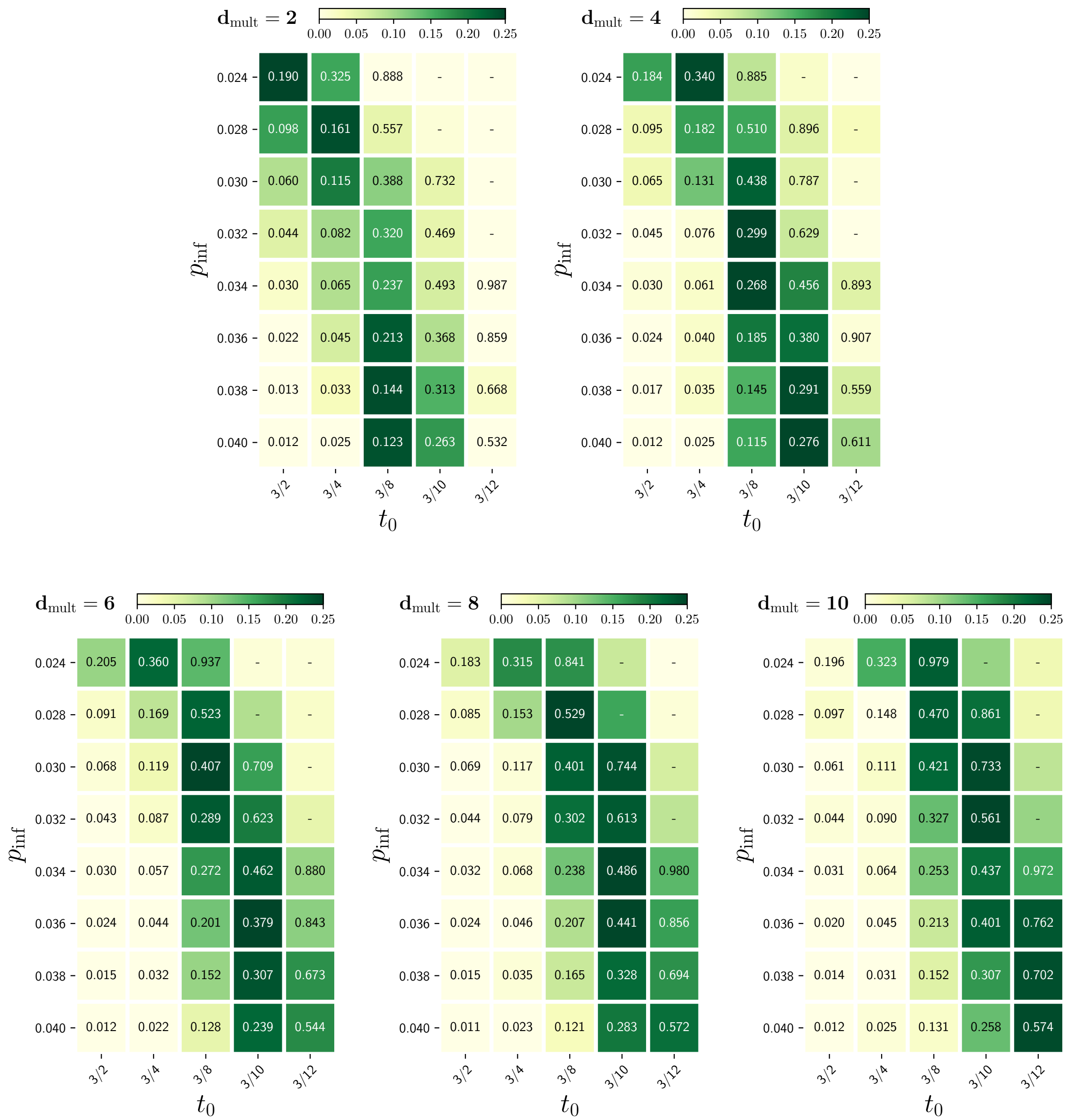

Figure 8: Estimated fraction of symptomatic infections that become documented in Uttar Pradesh as a function of $p_{\mathbf{inf}}$ (y axis) and t_0 (x axis). Each plot corresponds to a higher mortality multiplier $d_{\mathbf{mult}}$. Darker cells indicate better goodness of fit of the corresponding parameter settings to the true number of reported deaths on 10 April. A broad range of parameter combinations fit the data well, giving a very wide plausible range of 11.33%–99.54% for the documentation rate. This wide range is likely due to the small number of deaths that have been reported so far in the state, making precise parameter fits challenging to achieve.

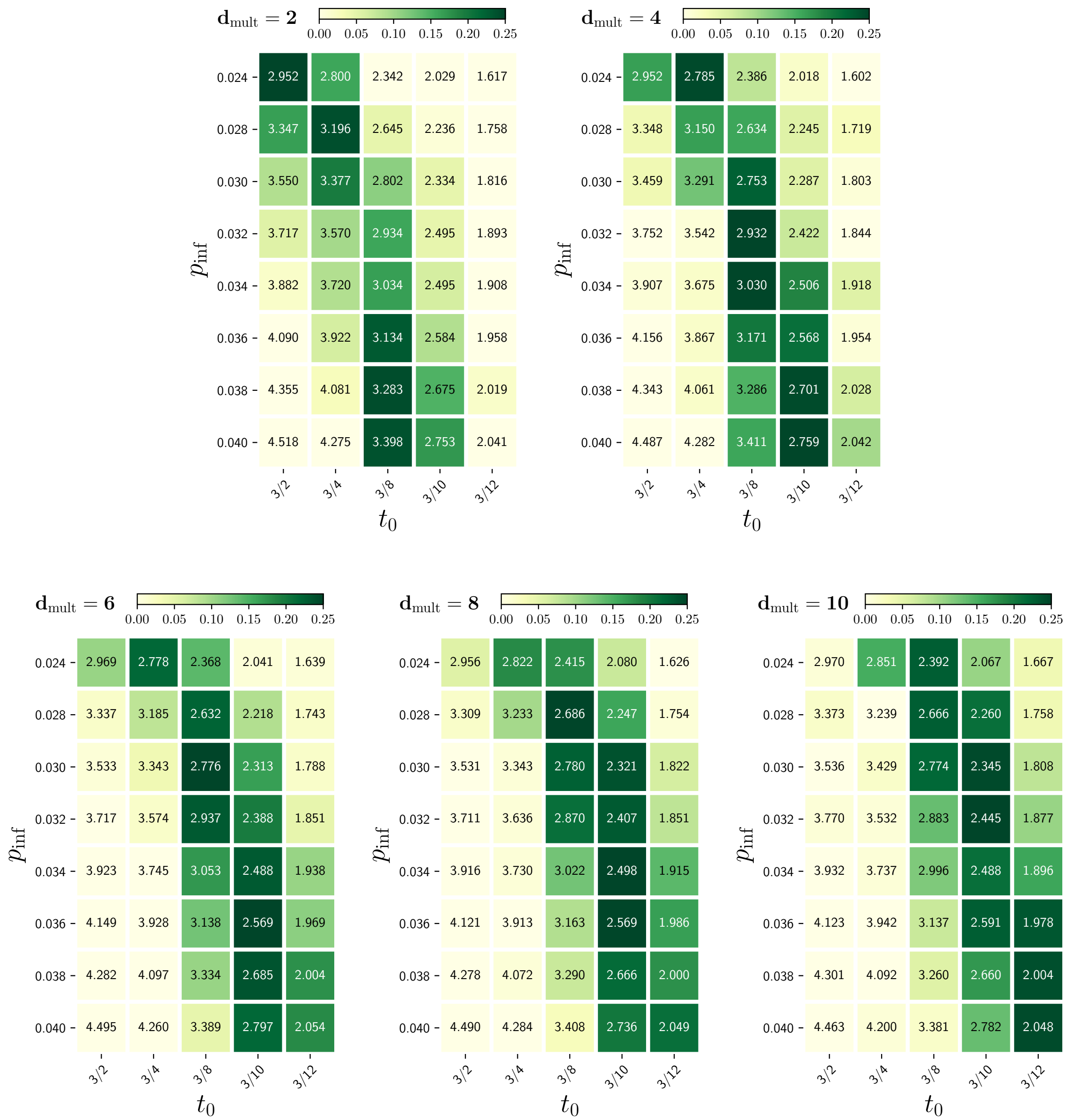

Figure 9: Estimated values of R_0 for Uttar Pradesh during the pre-lockdown phase as a function of $p_{\mathbf{inf}}$ (y axis) and t_0 (x axis). Each plot corresponds to a higher mortality multiplier $d_{\mathbf{mult}}$. Darker cells indicate better goodness of fit of the corresponding parameter settings to the true number of reported deaths on 10 April. A broad range of parameter combinations fit the data well, giving a plausible range of 1.97–3.46 for R_0.