

# Taming the pandemic by doing the mundane

Satarupa Bhattacharjee<sup>\*†1</sup>, Shuting Liao<sup>\*†2</sup>,  
Debashis Paul<sup>\*1</sup>, and Sanjay Chaudhuri<sup>\*‡3</sup>

<sup>1</sup>*Department of Statistics, University of California, Davis*

<sup>2</sup>*Graduate Group in Biostatistics, University of California, Davis*

<sup>3</sup>*Department of Statistics and Applied Probability, National University of Singapore*

## Abstract

We propose a network-based multi-compartment emulator for the COVID-19 pandemic spread by accounting for various epidemiological factors, and different intervention options like lockdown, testing and vaccination. Our model allows migrations across a network of nodes representing different population centers or strata. The focus is on making optimal decisions which, by making a meaningful assessment of the costs due to deaths, lockdowns and the capacity of the healthcare system, minimize the economic impact of the pandemic. Our results suggest that a combination of high rate of testing and rapid vaccination is very effective in bringing the pandemic under control quickly and economically.

**Keywords:** COVID-19, Multi-compartments dynamics, Time-dependent Compartments, Vaccination

---

<sup>\*</sup>Author contributions : S.B. - Algorithmic implementation and Coding, Manuscript preparation, Simulation study, Statistical summary and visualization; S.L. - Coding, Simulation study, Statistical summary and visualization; D.P. - Problem formulation, Manuscript editing, Advisory role; S.C. - Problem formulation, Algorithmic implementation, Manuscript editing, Advisory role.

<sup>†</sup>Joint first author

<sup>‡</sup>Corresponding author: stasc@nus.edu.sg

# 1 Introduction

The ongoing COVID-19 pandemic has posed one of the greatest challenges to humanity in recent times. The human cost in terms of lives lost to the pandemic has been staggering, as well as the economic cost for mitigation. Even though arrival of effective vaccines at the end of 2020 has raised hopes substantially in terms of finally bringing an end to the pandemic, inadequate vaccine availability coupled with distribution issues have contributed to the repeated surges at a global level. All of these have raised debates about the relative effectiveness of measures such as increased diagnostic testing and vaccination coupled with intervention measures. The latter includes restricting the social mobility by imposing lockdowns and strict masking mandates. The economic impact of various measures undertaken by governments brings about the unfortunate choice between saving lives versus preserving collective economic well-being (see e.g. [Mbwogge \(2021\)](#), [Cirakli et al. \(2021\)](#), [Bubar et al. \(2021\)](#), [Susskind and Vines \(2020\)](#), [Prem et al. \(2020\)](#), [Soltesz et al. \(2020\)](#)). Prioritizing the latter resulted in a few countries initially attempting to achieve “herd immunity” through unfettered propagation of virus in the community, typically with disastrous consequences for public health, and at no small cost to the economy ([Randolph and Barreiro \(2020\)](#), [Kwok et al. \(2020\)](#), [Brett and Rohani \(2020\)](#)).

These facts obviate the paramount importance of bringing all the elements – epidemiological, interventionist and economic – together in forming a policy decision, at a regional or national level. In addition, for an effective policy, it is necessary to also take into account factors like the intrinsic capacity of the healthcare system and differential levels of vulnerability to the disease among different segments of the population. However, in spite of voluminous research in the direction of both tracking and predicting the course of the pandemic, there is relatively little work addressing the question of appropriate policy decisions in terms of adopting specific intervention measures, while incorporating the different contributing factors as well as the economic impact.

The focus of this study is to find a policy decision in the form of an optimal degree of social

distancing, typically executed through a combination of lockdown and physical distancing. This optimal decision is obtained by minimizing a cost function that aims to limit total mortality and severe illness, consistent with the ultimate objective of most vaccine development (also see Ghosh (2021), Ghosh and Halder in this volume), while also being responsive to the economic costs of lockdown, under existing constraints in terms of the capacity of the healthcare system. The cost is aggregative over a fixed time horizon. We also investigate the impact of various rates of testing and vaccination, as well as different levels of migration.

In order to achieve this, we introduce a discrete-time deterministic dynamic model for the disease dynamics on a network, the nodes of which represent different geographical entities, or population segments, with differential levels of vulnerability to the disease. At the level of individual nodes, this is a compartmental model akin to SIR (Susceptible-Infected-Recovered) or SEIR (Susceptible-Exposed-Infectious-Removed) models popularly used in modeling the pandemic (see e.g. Tolles and Luong (2020), Giordano et al. (2020)). However, it incorporates the effects of migration (Kucharski et al., 2020) as well as social distancing on the dynamics (Badr et al., 2020). Moreover, the model admits the effect of testing and quarantining people, as well as vaccination. Specific rate parameters associated with the model are chosen by making use of analyses performed on the COVID-19 pandemic data in the USA in a companion paper (Bhattacharjee et al., 2021). Therefore, the model is expected to serve as a realistic emulator of this complex epidemiological process. The cost function for optimization, admittedly limited in its scope, is set as a sum of the loss of economic output resulting from deaths from the disease, and that from the spells of lockdown.

We perform a comprehensive set of simulations that idealize different scenarios and compare the corresponding optimal policy choices and their human and economic costs. The main conclusion of our analyses is that there is no stand-alone measure that can bring the pandemic under control within a reasonable time frame. Rather, it is necessary to combine a set of policy measures to limit the human and economic costs to a low level. Even then, there may be a

| Compartments         |   | Parameters                          |   |               |  |  |
|----------------------|---|-------------------------------------|---|---------------|--|--|
| Unobservable:        |   | Epidemiological: (Transition rates) |   | Intervention: |  |  |
| $S$                  | Susceptible   | $\gamma_k$                          | Asymptomatic to Symptomatic                       | $\omega_{jk}$ | Daily rate of migration from node $j$ to $k$ .   |  |
| $J$                  | Infected but asymptomatic                                       | $\alpha_k$                          | Asymptomatic to Recovered                         |               |  |  |
| $G$                  | Uninfected individuals quarantined due to a false positive test | $\zeta_k$                           | Recovery from symptomatic without hospitalization | $\omega_{jk}$ | $e^{(\beta_{0k} + \beta_{1k} \Delta D_{jt})} / \{1 + e^{(\beta_{0k} + \beta_{1k} \Delta D_{jt})}\}$      |  |
| Observable           |   | $\xi_k$                             | Symptomatic to Hospitalization                    | $\iota_{kt}$  | Infection rate at node $k$ at time $t$   |  |
| $I$                  | Symptomatic individuals   | $\rho_k$                            | Hospitalization to Recovered                      | $\iota_{kt}$  | $\iota_c \mu_{kt} J_{kt} / (S_{kt} + J_{kt} + R_{kt} + IV_{kt})$   |  |
| $D$                  | Death   | $\delta_k$                          | Mortality rate                                    | $\mu_{kt}$    | $\mu_k \kappa_{kt}^2$  |  |
| $IV$                 | Vaccinated  | $\iota_c$                           | Basic infection coefficient                       | $\mu_k$       | The number of people an average individual in node $k$ meets on a day in the absence of any restrictions |  |
| $H$                  | Hospitalised  | Clinical                            |   |               | $\kappa_{kt}$  | The fraction of people allowed outside within node $k$ , at time $t$ |
| $Q$                  | Quarantined   | $\phi_{kt}$                         | $\psi_F T_{kt} / (S_{kt} + J_{kt})$               |               |  |  |
| $T$                  | Tested  | $\tau_{kt}$                         | $\psi_T T_{kt} / (S_{kt} + J_{kt})$               |               |  |  |
| Partially Observable |   | $\psi_F$                            | True positive rate of test                        |               |  |  |
| $R$                  | Recovered   | $\psi_T$                            | False positive rate of the test                   |               |  |  |
|                      |   | $\nu_k$                             | Rate of vaccination at the $k$ th node            |               |  |  |

Table 1: Definition of the compartments and the epidemiological and intervention parameters. More details can be found in the Supplement ([add link](#)).

need for multiple rounds of lockdown to dampen the surges in infection. Moreover, even with vaccination, natural “herd immunity” is not a practical policy option even from an economic point-of-view if one carefully factors in the true economic costs. These conclusions are generally consistent with the experience across the world. Therefore, it is expected that the proposed framework can act as a useful workbench for health policy options at local or regional levels in addressing the enormous challenges posed by the pandemic.

## 2 Mechanistic model for a viral epidemic

### 2.1 Compartments of the system

We propose a network-based multi-compartmental model to mimic the progression of a pandemic in terms of various observable and partially or totally unobservable compartments. We consider a network of  $N$  nodes, each representing a population center (e.g. town, district, state or country) with different nodes possibly having different levels of vulnerability to the disease. The model incorporates migration among the nodes.

We use  $t$  to denote time (in days), and  $k$  to denote nodes. Specifically, for node  $k$ ,  $D_{kt}$

denotes the number of deaths up to time  $t$ . Notations for other compartments are similar. The epidemic dynamics is assumed to be memoryless, meaning that the compartment transition rates are independent of the duration of stay in a particular compartment. Definitions of the compartments and the epidemiological and intervention parameters are given in Table 1. More detailed definitions and underlying model assumptions are given in Section 1 of the Supplementary material ([add link](#)). Note that, our model does not include a pre-symptomatic compartment, which is neither observable nor identifiable from the available data for COVID-19.

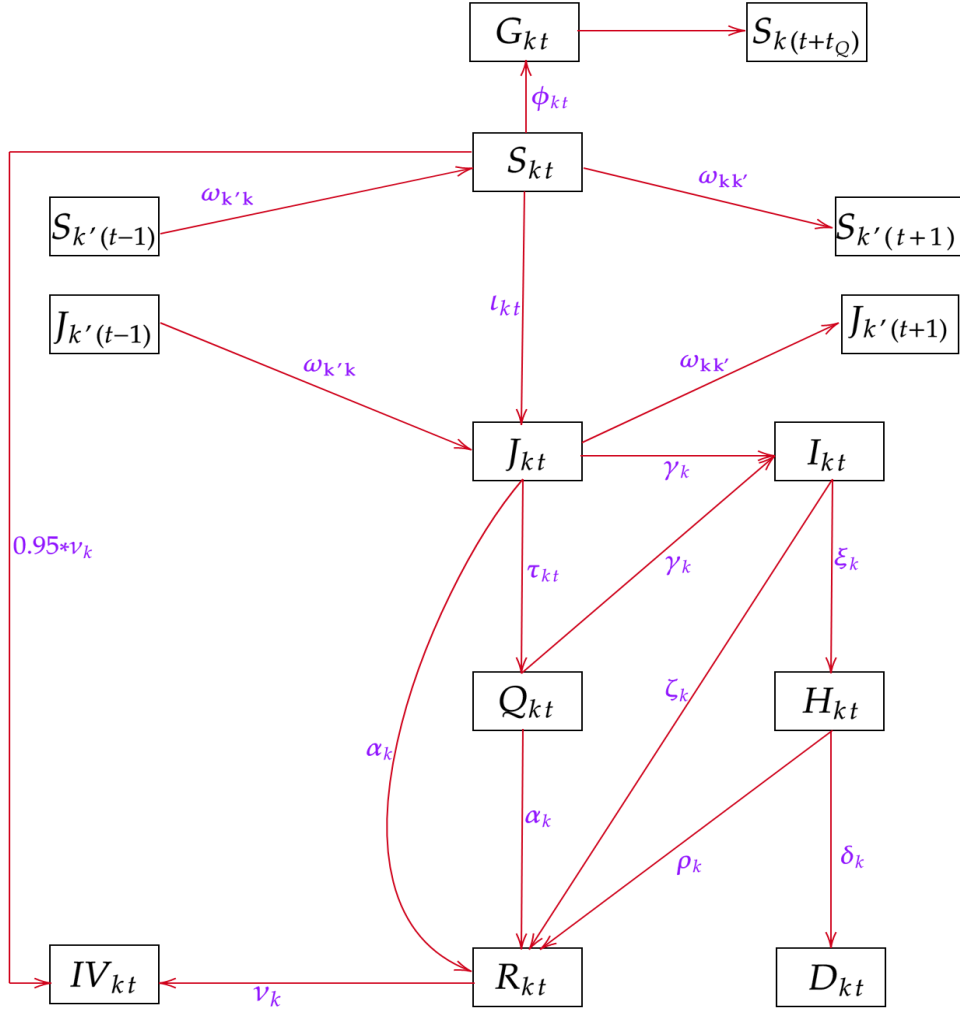


Figure 1: Diagram showing the different stages of the propagation of the pandemic for the  $k^{\text{th}}$  node at time  $t$ .

### 3 Description of the dynamics

The evolution of the pandemic is expressed mechanistically through equations (1)–(9). They capture the mean daily change in the values of the compartments. A graphical representation of the proposed disease propagation model is presented in Figure 1.

A key model assumption is that all infected individuals are initially asymptomatic, after which they either start to show symptom, get tested and quarantined, or recover directly. The disease spreads through the asymptomatic but infected individuals. We assume that uninfected individuals, falsely caught in the quarantine net, join the susceptible population after  $t_Q$  days after isolating themselves. Both susceptible ( $S$ ) and recovered ( $R$ ) groups are vaccinated, with the vaccination efficacy assumed to be 95% and 100% for these groups, respectively. Once vaccinated the individuals play no further role in the progression of the epidemic. Our model ignores birth and deaths due to other causes (Ivorra et al., 2020). Migration (with time dependent rate) is only allowed for the susceptible and asymptomatic populations of the nodes.

$$\Delta S_{kt} = \sum_{j:j \neq k} \omega_{jk} S_{jt} - \sum_{j:j \neq k} \omega_{kj} S_{kt} - (\iota_{kt} + \phi_{kt} + 0.95\nu_k) S_{kt} + G_{k(t-t_Q)}, \quad (1)$$

$$\Delta J_{kt} = \sum_{j:j \neq k} \omega_{jk} J_{jt} - \sum_{j:j \neq k} \omega_{kj} J_{kt} - (\tau_{kt} + \gamma_k + \alpha_k) J_{kt} + \iota_{kt} S_{kt}, \quad (2)$$

$$\Delta G_{kt} = \phi_{kt} S_{kt} - G_{k(t-t_Q)}, \quad (3)$$

$$\Delta I_{kt} = \gamma_k (J_{kt} + Q_{kt}) - (\zeta_k + \xi_k) I_{kt}, \quad (4)$$

$$\Delta Q_{kt} = \tau_{kt} J_{kt} - (\gamma_k + \alpha_k) Q_{kt}, \quad (5)$$

$$\Delta H_{kt} = \xi_k I_{kt} - (\rho_k + \delta_k) H_{kt}, \quad (6)$$

$$\Delta R_{kt} = \alpha_k (J_{kt} + Q_{kt}) + \zeta_k I_{kt} + \rho_k H_{kt} - \nu_k R_{kt}, \quad (7)$$

$$\Delta IV_{kt} = 0.95\nu_k S_{kt} + \nu_k R_{kt}, \quad (8)$$

$$\Delta D_{kt} = \delta_k H_{kt}. \quad (9)$$

## 4 Intervention through optimal lockdown

Other than vaccination, imposition of a lockdown with various severity has been useful in controlling the spread of the pandemic. Lockdowns have evidently reduced the social interaction and possibility of disease spread by asymptomatic individuals, resulting in lower deaths and hospitalizations. However, economic costs of such lockdowns have also come under focus. Inadequate economic support during the lockdown can lead to serious socio-economic problems. The mass migration of workers in India during the nationwide lockdown in 2020, and the staggering number of deaths in the second wave in 2021, when lockdowns were localized and mostly delayed, have abundantly displayed the degree of humanitarian crises associated with unplanned lockdowns. A cost-balanced strategy for imposing lockdowns should therefore be quite beneficial.

We devise an optimal lockdown strategy by combining two considerations. A lockdown is imposed whenever either the node-specific hospitalization rate exceeds a certain threshold  $\eta_{kt}$ , or the number of symptomatic people exceed a certain fixed lower bound. The severity of the lockdown is controlled by the social distancing parameter  $\kappa_{kt}$  (between 0 and 1, with 0 indicating complete lockdown). The optimal choice of  $(\eta_{kt}, \kappa_{kt})$  ensures that at all times and at all nodes, the hospital capacity (assumed 0.5% of the nodal population) is never exceeded. This is achieved by solving the constrained optimization problem:

$$\left\{ \begin{array}{l} (\hat{\kappa}_{kt}, \hat{\eta}_{kt}) = \underset{(\kappa_{kt}, \eta_{kt})}{\operatorname{argmin}} \Phi(\kappa_{kt}, \eta_{kt}) \text{ such that } 0 \leq \kappa_{kt}, \eta_{kt} \leq 1, \text{ and} \\ \text{the proportion of hospitalised stays below 0.005, for all } k \text{ and } t. \end{array} \right. \quad (10)$$

The objective function  $\Phi(\kappa_{kt}, \eta_{kt})$  balances the economic cost of death with that of the cost of lockdown. In particular we define:

$$\Phi(\kappa_{kt}, \eta_{kt}) = \frac{1}{W} \times \frac{\sum_{k=1}^N D_{kT}(\kappa_{kt}, \eta_{kt})}{\sum_{k=1}^N S_{k1}} + \frac{\sum_{k=1}^N \sum_{t=1}^T C_{kt}(\kappa_{kt}, \eta_{kt})}{\sum_{k=1}^N S_{k1}}. \quad (11)$$

The economic cost of the lockdown is represented by the term:

$$C_{kt}(\kappa_{kt}, \eta_{kt}) = \begin{cases} \frac{(1-\kappa_{kt})(S_{kt}+J_{kt}+R_{kt}+IV_{kt})}{30 \times 365}, & \text{whenever a lockdown is imposed,} \\ 0 & \text{otherwise.} \end{cases} \quad (12)$$

This cost function comprises of the economic cost borne by those among susceptible, asymptomatic, recovered and immunized people whose work opportunities are lost during lockdown periods. On day  $t$  at node  $k$ , the fraction among these groups losing their job opportunities is  $(1 - \kappa_{kt})$ . The factor 365 in the denominator  $30 \times 365$  signifies the fact that the economic cost is measured in terms of loss of per-capita annualized GDP, while the factor 30 is the (assumed) expected number of additional years a person may live, if he/she does not succumb to the disease. This effectively means, in this cost calculation we equate each death to a loss of 30 years of per-capita GDP. In practice, policymakers may give different relative importance to death vis-a-vis the economic cost of lockdown. This is incorporated in (11) by the positive factor  $W$ . A smaller value of  $W$  signifies a greater relative weight on the number of deaths.

## 5 Case studies

To explore the effects of testing and vaccination we perform a simulation study by generating the compartmental trajectories from the proposed model. The analyses are carried out over a time horizon of  $T = 400$  days, using the epidemiological parameters given in Table 2. Population sizes and initial values for the nodes are in Table 3. The number of daily tests  $T_{kt}$  is assumed to grow daily by 3% until it reaches a maximum value.

| Epidemic parameter | $\iota_c$ | $\gamma$ | $\alpha$ | $\zeta$ | $\xi$ | $\rho$ | $\delta$ |
|--------------------|-----------|----------|----------|---------|-------|--------|----------|
| Vulnerable node    | 0.1       | 0.03     | 0.005    | 0.05    | 0.2   | 0.07   | 0.03     |
| Robust node        | 0.1       | 0.01     | 0.02     | 0.1     | 0.1   | 0.15   | 0.03     |

Table 2: The epidemic parameters for the nodes in the case studies.



| Node $k$        | 1          | 2      | 3      | 4      | 5      | 6      | 7      | 8      | 9      | 10     |
|-----------------|------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Type            | Vulnerable |        |        |        |        | Robust |        |        |        |        |
| $S_{k1}$        | 450000     | 449900 | 450000 | 350000 | 350000 | 350000 | 350000 | 350000 | 250000 | 250000 |
| $J_{k1}$        | 0          | 100    | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0      |
| Tests, $T_{k1}$ | 1000       | 1000   | 1000   | 1000   | 1000   | 500    | 500    | 500    | 500    | 500    |
| $\mu_k$         | 3          | 3      | 3      | 3      | 3      | 5      | 5      | 5      | 5      | 5      |

Table 3: Initial value (on day  $t = 1$ ) of the number of susceptible  $S_{k1}$  and asymptomatic but infected people  $J_{k1}$  for each node  $k$ .

We consider six scenarios described in Table 4. Comparative summaries including the across-node maximums of peak hospitalization, deaths and peak quarantined population are displayed in Table 5. The optimal values of length, severity and threshold parameters for imposing a lockdown, the resulting total economic cost, and total deaths, are displayed in Table 6.

| Scenario  |                  | 1     | 2     | 3    | 4    | 5     | 6     |
|---|------------------|-------|-------|------|------|-------|-------|
| Type  | Lockdown         | No    | No    | Yes  | Yes  | Yes   | Yes   |
|   | Vaccination      | No    | Yes   | No   | Yes  | No    | Yes   |
|   | Testing          | High  | High  | Low  | Low  | High  | High  |
| Vaccination rate, $\nu_k$   | Vulnerable nodes | 0     | 0.02  | 0    | 0.02 | 0     | 0.02  |
|   | Robust nodes     | 0     | 0.01  | 0    | 0.01 | 0     | 0.01  |
| Max testing capacity per day  |                  | 20000 | 20000 | 5000 | 5000 | 20000 | 20000 |
| Daily growth of testing=3%, $\psi_T = 0.99$ , $\psi_F = 0.02$ , $\omega_{jk} \in (10^{-5}, 10^{-4})$ , $W = 30$ |                  |       |       |      |      |       |       |

Table 4: Vaccination rates and daily testing capacities under different scenarios considered in the six cases studies.

| Scenario | Max H         |             | Max D         |             | Max Q         |              |
|----------|---------------|-------------|---------------|-------------|---------------|--------------|
|          | Vulnerable    | Robust      | Vulnerable    | Robust      | Vulnerable    | Robust       |
| 1        | 55258(12.28%) | 7041(2.01%) | 90108(20.02%) | 3684(1.05%) | 56151(12.48%) | 31029(8.87%) |
| 2        | 27413(6.09%)  | 5327(1.52%) | 49494(11.00%) | 2843(0.81%) | 28023(6.23%)  | 24703(7.06%) |
| 3        | 604(0.13%)    | 1746(0.05%) | 4210(0.94%)   | 2603(0.74%) | 637(0.14%)    | 16624(4.75%) |
| 4        | 1096(0.24%)   | 1749(0.05%) | 2832(0.63%)   | 1836(0.52%) | 893(0.02%)    | 13163(3.76%) |
| 5        | 188(0.04%)    | 181(0.05%)  | 746(0.17%)    | 194(0.06%)  | 198(0.04%)    | 1463(0.42%)  |
| 6        | 421(0.09%)    | 733(0.21%)  | 1061(0.24%)   | 664(0.19%)  | 461(0.13%)    | 5739(1.64%)  |

Table 5: Maximum values of  $H$ ,  $D$  and  $Q$  among vulnerable and robust nodes, respectively. Percentages out of the population (for the node with the maximum value) are in parentheses.

| Scenario | Optimal parameter              |                       | Max Total Lockdown Duration (days) |        | Economic cost of Lockdown (% of GDP) | Total Death     |
|----------|--------------------------------|-----------------------|------------------------------------|--------|--------------------------------------|-----------------|
|          | $(\kappa_v, \kappa_r)$         | $\eta$                | Vulnerable                         | Robust |                                      |                 |
| 1        | (1,1)                          | 1                     | 0                                  | 0      | 0                                    | 429137 (11.92%) |
| 2        | (1,1)                          | 1                     | 0                                  | 0      | 0                                    | 242022 (6.72%)  |
| 3        | (0.36, 0.36)                   | $1 \times 10^{-4}$    | 387                                | 368    | 57.32                                | 30272 (0.84%)   |
| 4        | (0.25, 0.29)                   | $3.57 \times 10^{-4}$ | 143                                | 192    | 28.44                                | 20806 (0.58%)   |
| 5        | (0.28, $7.76 \times 10^{-5}$ ) | $5.58 \times 10^{-5}$ | 317                                | 305    | 63.25                                | 3951 (0.11%)    |
| 6        | (0.18, 0.23)                   | $1.69 \times 10^{-4}$ | 115                                | 152    | 24.73                                | 7281 (0.20%)    |

Table 6: Optimal parameters, maximums of total lockdown duration for the vulnerable and robust are shown respectively. The economic cost of lockdown (as annualized % of GDP) and total death of all nodes are also reported.

## 5.1 A shot at herd immunity

In the early days of the COVID-19 pandemic, a quick attainment of the herd immunity by not imposing any restrictions was considered as a potential policy choice in many countries. This choice was supposed to cause the least economic distress and would have made the population immune (through recovery after infection) within the fastest time span. Even though a large number of deaths and a possible collapse of the healthcare infrastructure were postulated, this policy was initially adopted or considered in some countries, including Sweden and the UK.

From Figures 2 and 3, the devastating cost of such a policy is evident. Without a lockdown, the number of susceptible falls exponentially fast, as essentially everyone in the populations is exposed to the spread of the disease, and the pandemic runs its course within the first 100 days. This however, comes at a terrible cost in terms death and hospitalization. Without vaccination, even with high testing (Scenario 1), Tables 5, 6 and Figure 2 show that approximately 12% of the population is likely to succumb to the disease. The death is particularly high in the vulnerable population, where nearly 20% people are expected to die. At its peak almost 12% and 2% of the population are expected to be hospitalised in the vulnerable and robust nodes, respectively. By any standards, these numbers paint a catastrophic picture, and is well beyond the capacity of any country’s healthcare system. The countries with large elderly and susceptible population are expected to be more severely hit. Swedish policy of attaining a fast herd immunity has been controversial. It has severely stretched medical facilities, and it is largely accepted that Sweden

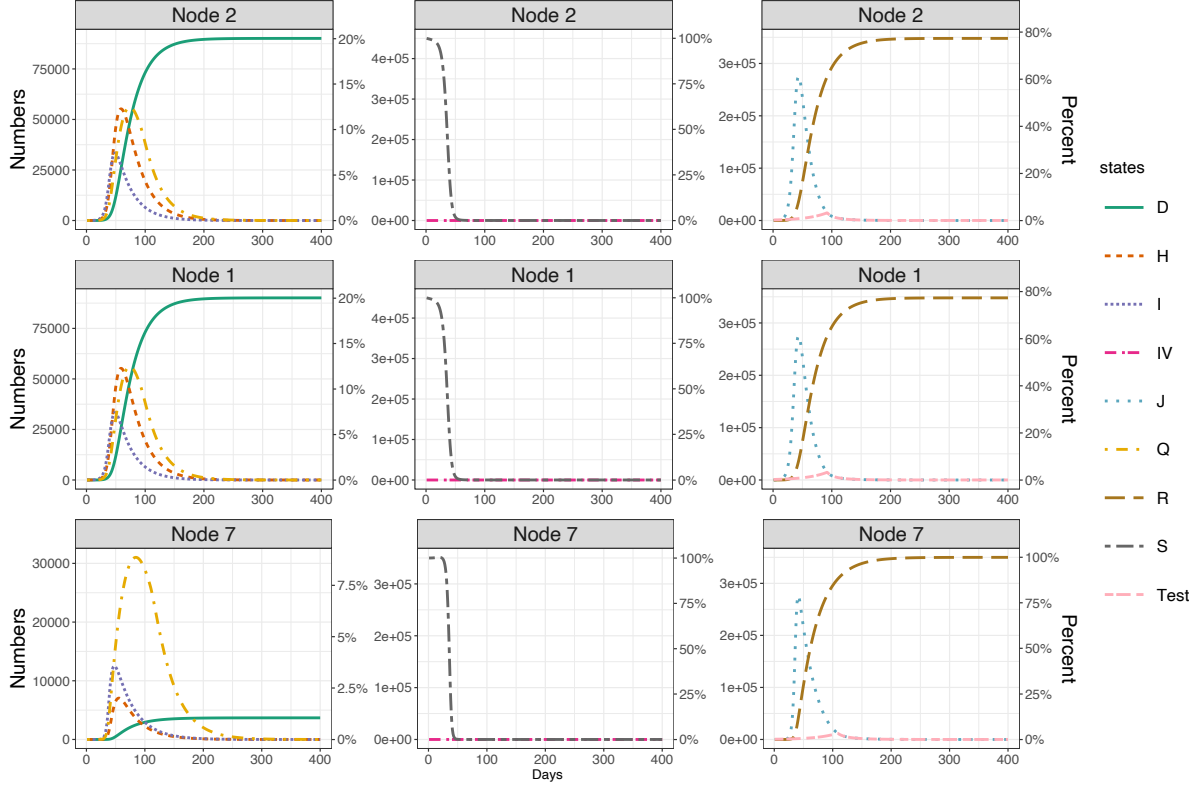


Figure 2: Scenario 1: Trajectories resulting from an attempt at achieving herd immunity with high level of testing, but without lockdown or vaccination.

has fared worse compared to other Scandinavian countries which chose a more conservative approach. In addition, delayed introduction of lockdown has resulted in severe shortage of hospital beds in countries including the UK (in 2020) and India (in 2021).

Introduction of vaccination on the 10-th day after the onset (Scenario 2) does not improve the results significantly. Even though the total number of deaths reduce to 6.7%, it is still unacceptably high. In the vulnerable nodes around 11% of the population perishes. At the epidemic's peak, the hospitalization is about 6% in the vulnerable nodes and 1.5% in the robust nodes, which far exceeds the assumed maximum hospital capacity of 0.5% of the population.

Even though no lockdown means no economic cost due to lost employment and business (see Table 6)\*, the true cost of achieving a fast herd immunity is catastrophic. Assuming that each

---

\*For simplicity, we exclude medical costs and closure to business due to infections (Ghosh, (2021), this volume.)

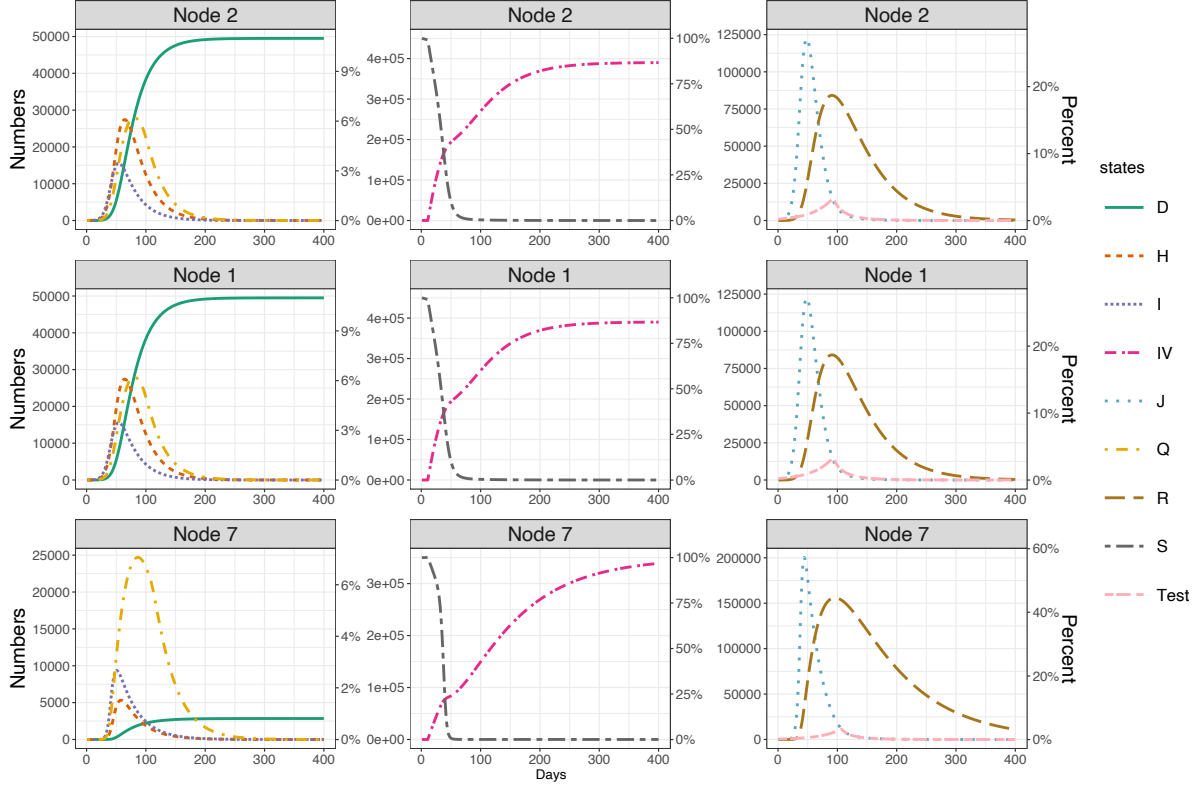


Figure 3: Scenario 2: Trajectories when no lockdown is allowed, but testing is high and vaccination starts on the 10-th day into the pandemic.

person dying has 30 additional years to live, with 11.92% death the total cost to the economy is 357.6% and 201.6% of the annual GDP in Scenarios 1 and 2, respectively. By comparing the economic costs of policies with optimal lockdown in Table 6, it becomes evident that the policy of achieving herd immunity fast without a lockdown is not even economically viable.

In both Scenarios 1 and 2, the robust nodes are also severely affected. Comparing with the optimal values of  $(\kappa_v, \kappa_r)$  in other scenarios, it appears that a policy of isolating the vulnerable population with a lockdown but leaving the robust population free of restrictions, does not seem to be viable either. Indeed, from the scenarios discussed below, it seems the optimal lockdown strategy is often harsher in the robust nodes than the vulnerable nodes.

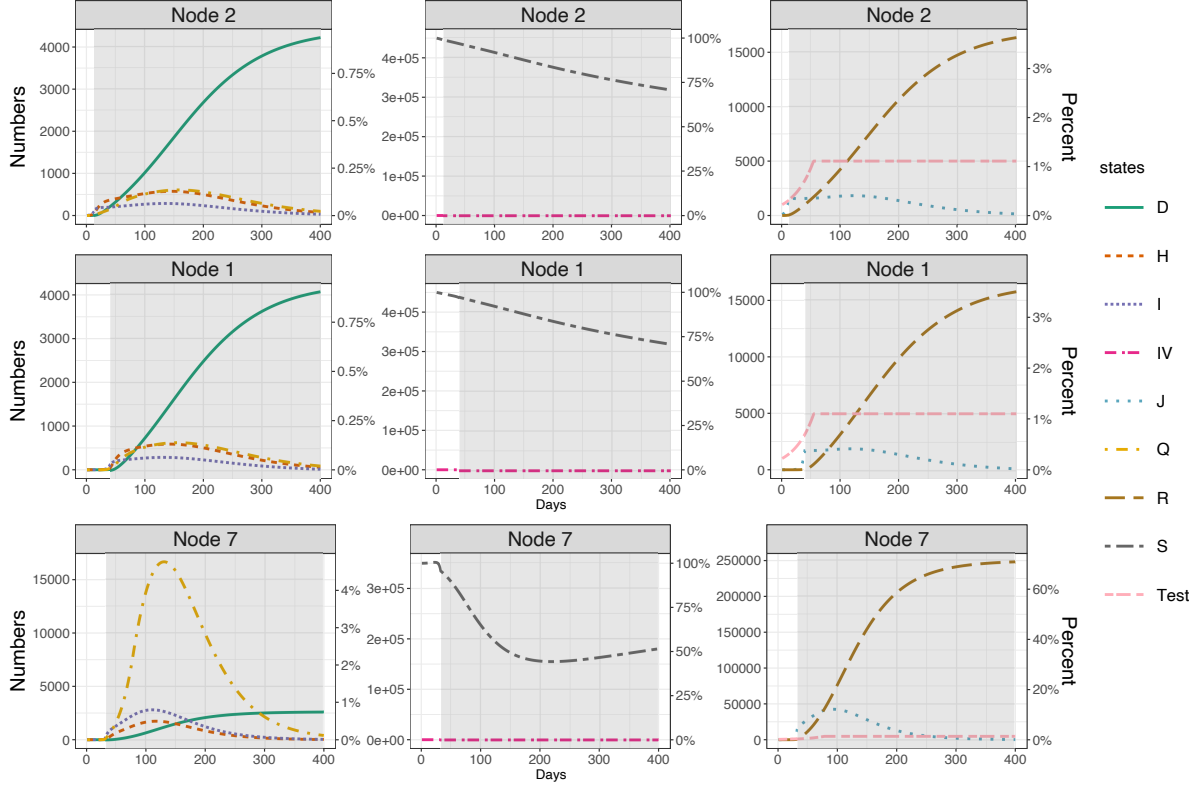


Figure 4: Scenario 3: Trajectories under a low testing regime and no vaccination.

## 5.2 Optimal lockdown in a low testing regime

Importance of mass testing and isolation of discovered cases through quarantines was emphasized by WHO and several medical organisations from the early days of the pandemic. However, prevalence and effectiveness of testing in different countries have varied. Countries like Taiwan, South Korea, Germany, Iceland etc. could scale up testing to cover a huge part of their population, while in many other countries, like the UK, India etc., much smaller portion of the population could be tested.

In Scenarios 3 and 4, the daily testing was capped at 5000 per node. Without the availability of vaccines, the proposed optimal strategy is to impose a long lockdown (387 days in vulnerable and 368 days in the robust nodes). The pandemic does not end within 400 days. The susceptible population decreases quite slowly in the vulnerable nodes. In the robust nodes, the susceptible

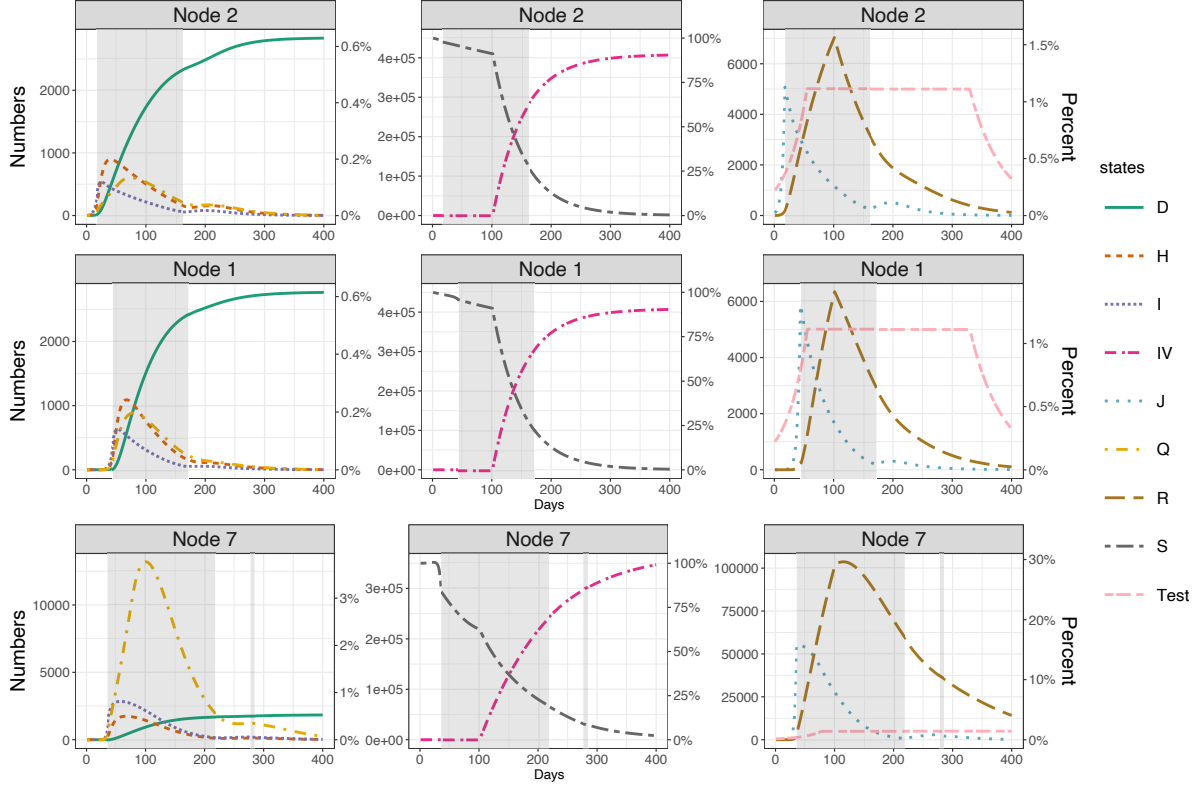


Figure 5: Scenario 4: Trajectories when vaccines are rolled out in a low testing regime

population initially decreases fast, followed by a sharp increase in latter stages primarily due to migration. The total mortality is low (0.84%), however the peak hospitalization in the robust nodes reaches the maximum capacity of 0.5% (of the population). The peak quarantine rate is also quite high at 4.75%.

With vaccination starting on the 100-th day, situation shows a marked improvement. Short lockdown phases of 143 and 192 days, respectively, in the vulnerable and robust nodes, seem to reduce the number of susceptible persons fast within 400 days. The lockdown needs to be more severe than the settings with no vaccination (see Table 6). However, the economic cost due to lockdown halves. The overall death percentage also reduces to 0.58%. Peak hospitalization in the robust nodes still reaches the assumed capacity (0.5%), however.

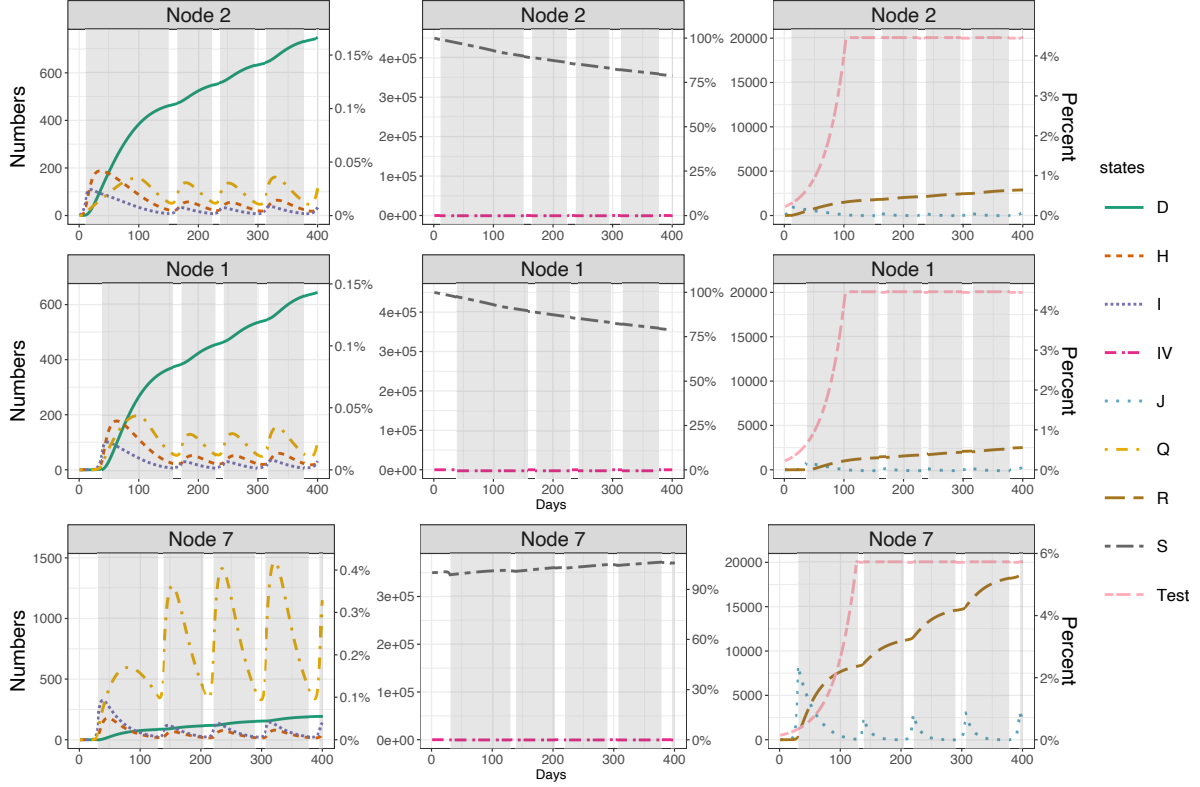


Figure 6: Scenario 5: Trajectories in a high testing paradigm, with no vaccination

### 5.3 Optimal lockdown in a high testing regime

We now consider the scenario where the maximum daily testing quickly increases daily by 3% to 20000. With no vaccination, like in Scenarios 5, the pandemic does not end within 400 days. But instead of a long, less severe lockdown, the optimal strategy involves repetitive lockdown phases, shown in Figure 6. The total lockdown duration is shorter than in Scenario 3, especially in the robust nodes. However, compared to Scenario 3, peak hospitalization rate and mortality are markedly lower. Even though fewer days are spent under lockdown, their increased severity (smaller values of  $(\kappa_v, \kappa_r)$ ) results in a higher economic cost. Interestingly, the susceptible populations in the robust nodes actually show a slow increase.

With vaccination starting on the 100-th day, the situation improves significantly. In Scenario 6, the optimal strategy involves a relatively modest initial lockdown period of 115 and 152 days

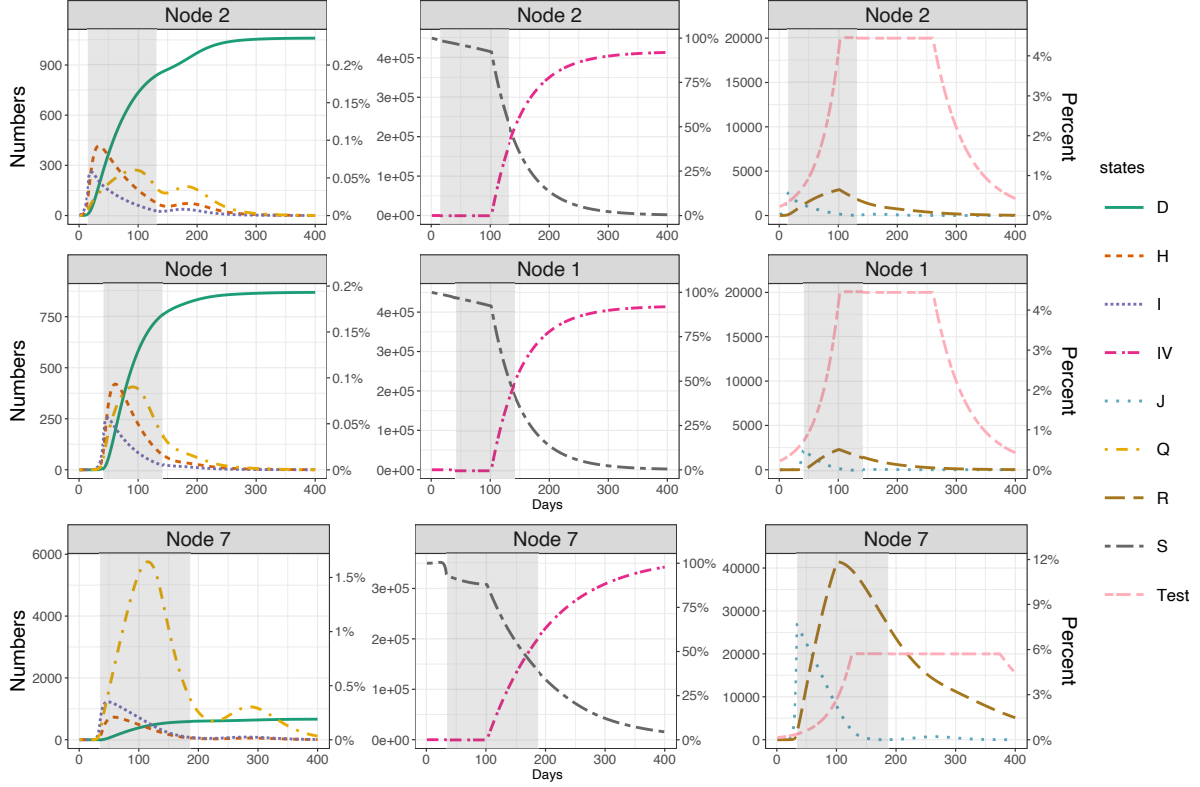


Figure 7: Scenario 6: Trajectories under a combination of high daily testing and vaccination.

in the vulnerable and robust nodes, respectively. Once the vaccination starts, the susceptible population decreases exponentially and the number of infected reduces to zero within an year. Even though compared to Scenario 5, number of deaths, peak hospitalisations and peak quarantines are higher (see Table 5), the economic cost due to lockdown is much lower. In fact, it is even lower than the economic cost for Scenario 4.

## 6 Discussion

Many aspects of the COVID-19 pandemic are still shrouded in mystery. Roll-out of several vaccines have provided some hope of that the end of the pandemic may be near. This is especially true in USA, where many restrictions like mask wearing, social distancing are being withdrawn. Our case studies show that even though without mass vaccination the pandemic will not end,



however, this is not enough in controlling the spread of the disease. Carefully designed lockdowns are very effective in dampening the spread of infections and providing relief to the healthcare system. Countries like Israel, UK, Chile and USA have been able to achieve a high vaccination rate. However, given the uncertainty in the effectiveness of the vaccines in preventing infections by mutant forms of the virus, the necessity of imposing periodic lockdown remains.

Our study clearly demonstrates the disastrous consequences of the strategy of attaining “herd immunity”. In fact, except Sweden no country seems to have chosen that path. Positive effects of a strict lockdown in controlling the pandemic in a relatively short time were observed in countries like China, Australia, and New Zealand. Moreover, many countries like Spain, Iran, Italy, Denmark, Germany, UK, India etc. have imposed multiple phases of lockdown. Most of these lockdown measures have been imposed to address immediate healthcare crises without any known discernible strategy regarding economic planning.

Our analyses show that a combination of “mundane” strategies like extensive diagnostic testing, periodic lockdown and vaccination is the key to control and finally eradicate a destabilizing pandemic like COVID-19. Furthermore, optimal strategies can be devised to minimize the economic cost due to lockdown, limit the number of deaths, and relieve the stress on the health infrastructure. By modifying migration policies, node compositions, and the relative importance of deaths in the proposed cost function, the proposed model can be used to suit many population structures and scenarios that may emerge in future. Finally, a policy which solely relies on testing and vaccination, but no lockdown, is much more damaging in both health and economic terms than a policy that optimally combines all the possible interventions.

## **Reproducibility**

The R codes necessary for replicating our results are collated in the github page

[https://github.com/Satarupa3671/Mechanistic\\_Model\\_COVID19.git](https://github.com/Satarupa3671/Mechanistic_Model_COVID19.git).

## Acknowledgements

The authors would like to thank Professor Prabir Burman for helpful discussions. Shuting Liao was partially supported by the NASA-TRISH grant 19-19BRASH-2-0055. Debashis Paul was partially supported by the NSF grants DMS-1713120, DMS-1811405 and DMS-1915894, and the NASA-TRISH grant 19-19BRASH-2-0055. Sanjay Chaudhuri was partially supported by the MOE Singapore AcRF grants R155000194114 and R155000215114.

## References

- Badr, H. S., H. Du, M. Marshall, E. Dong, M. M. Squire, and L. M. Gardner (2020). Association between mobility patterns and covid-19 transmission in the usa: a mathematical modelling study. The Lancet Infectious Diseases 20(11), 1247–1254.
- Bhattacharjee, S., S. Liao, D. Paul, and S. Chaudhuri (2021). Inference on the dynamics of the covid pandemic from observational data. medRxiv.
- Brett, T. S. and P. Rohani (2020). Transmission dynamics reveal the impracticality of covid-19 herd immunity strategies. Proceedings of the National Academy of Sciences 117(41), 25897–25903.
- Bubar, K. M., K. Reinholt, S. M. Kissler, M. Lipsitch, S. Cobey, Y. H. Grad, and D. B. Larremore (2021). Model-informed covid-19 vaccine prioritization strategies by age and serostatus. Science 371(6532), 916–921.
- Cirakli, U., I. Dogan, and M. Gozlu (2021). The relationship between covid-19 cases and covid-19 testing: a panel data analysis on oecd countries. Journal of the Knowledge Economy, 1–14.
- Giordano, G., F. Blanchini, R. Bruno, P. Colaneri, A. Di Filippo, A. Di Matteo, and M. Colaneri (2020). Modelling the covid-19 epidemic and implementation of population-wide interventions in italy. Nature medicine 26(6), 855–860.
- Ivorra, B., M. R. Ferrández, M. Vela-Pérez, and A. Ramos (2020). Mathematical modeling of the spread of the coronavirus disease 2019 (covid-19) taking into account the undetected infections. the case of china. Communications In Nonlinear Science And Numerical Simulation 88, 105303.
- Kucharski, A. J., T. W. Russell, C. Diamond, Y. Liu, J. Edmunds, S. Funk, R. M. Eggo, F. Sun, M. Jit, J. D. Munday, et al. (2020). Early dynamics of transmission and control of covid-19: a mathematical modelling study. The lancet infectious diseases 20(5), 553–558.

- Kwok, K. O., F. Lai, W. I. Wei, S. Y. S. Wong, and J. W. Tang (2020). Herd immunity—estimating the level required to halt the covid-19 epidemics in affected countries. Journal of Infection 80(6), e32–e33.
- Mbwogge, M. (2021). Mass testing with contact tracing compared to test and trace for the effective suppression of covid-19 in the united kingdom: Systematic review. JMIRx med 2(2), e27254.
- Prem, K., Y. Liu, T. W. Russell, A. J. Kucharski, R. M. Eggo, N. Davies, S. Flasche, S. Clifford, C. A. Pearson, J. D. Munday, et al. (2020). The effect of control strategies to reduce social mixing on outcomes of the covid-19 epidemic in wuhan, china: a modelling study. The Lancet Public Health 5(5), e261–e270.
- Randolph, H. E. and L. B. Barreiro (2020). Herd immunity: understanding covid-19. Immunity 52(5), 737–741.
- Soltesz, K., F. Gustafsson, T. Timpka, J. Jaldén, C. Jidling, A. Heimerson, T. B. Schön, A. Spreco, J. Ekberg, Ö. Dahlström, F. Bagge Carlson, A. Jöud, and B. Bernhardsson (2020). The effect of interventions on covid-19. Nature 588(7839), E26–E28.
- Susskind, D. and D. Vines (2020). The economics of the covid-19 pandemic: an assessment. Oxford Review of Economic Policy 36(Supplement\_1), S1–S13.
- Tolles, J. and T. Luong (2020). Modeling epidemics with compartmental models. Jama 323(24), 2515–2516.