

## Containing Covid: "To trace or not to trace?" - That is not the question!

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The sudden onset of the Covid-19 pandemic disrupted the modern multi-national interconnected society and led the countries and societies to enforce unprecedented restrictions on movement. Among myriad containment measures, the policy of trace and quarantine found universal adoption among countries; the swift adoption of the policy was soon met with widespread criticism and opposition activists who questioned the utility and the risk associated with such a large scale collection of data and infringement on the movement of individuals. Consequently, one often tends to be either pro- or anti-trace and quarantine; the ensuing polarizing and politicized left little room for nuance. In this work, we undertake a methodology study to understand the nuances of the impact of different implementations of trace and quarantine. To this end, we design a user-friendly and intuitive tool that can be employed by experts to model the disease dynamics and societal structure. We focus on the study of the cost of policy with respect to quarantine degree, which captures the distance between the person required to quarantine after a person is detected to be infected. Our study results in a surprising conclusion: the cost is not necessarily monotone with respect to the degree of quarantine. Our analysis indicates that governments must curb the urge to adopt simplistic policy and the optimal policy of trace and quarantine for a country strongly depends on its societal structure and disease dynamics.

Additional Key Words and Phrases: Epidemics, Optimal Policy, Trace and Quarantine strategy, Agent networks

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### 1 INTRODUCTION

- 2 The interconnected nature of modern multi-national society acted as a strong catalyst in the pandemic of the Covid-19.
- 3 The sudden onset of Covid-19 pandemic disrupted sophisticated human societies in all aspects: the high mortality
- 4 among elder groups led to a stress on healthcare infrastructure that required the governments to take strong actions to
- 5 curb the spread of the virus.<sup>[8]</sup> As such, the governments all over the world scrambled to devise policy to contain and
- 6 mitigate the spread of virus <sup>[9, 26]</sup>. The inter-connected society was soon confronted with unprecedented restrictions
- 7 of the movement at a global scale not witnessed in over half a century. <sup>[27]</sup>
- 8 Among the many policies employed by the governments, the policy of trace and quarantine (albeit in different forms)
- 9 found near-universal adoption among the governments. Broadly, the policy of trace and quarantine focused on the

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10 usage of surveillance techniques to re-trace the movements of a confirmed infected patients to identify other close  
11 contacts. Once such close contacts are identified, the individuals in the contact graphs are often asked/required to  
12 (self-)quarantine. It is worth observing that the implementations of trace and quarantine have differed across countries:

13 • United States and England recommended quarantine of close contacts of the infected patients [7].  
14 • Some states in India focused on tracing and quarantining contacts up to two degrees of identified cases, i.e.,  
15 direct contacts of the infected patients[13, 31].  
16 • Vietnam, on the other hand, has focused on tracing and quarantining contacts up to three degrees of identified  
17 cases [5].

18 While the policy of trace and quarantine found universal adoption, its impact on the containment and mitigation  
19 varied across the countries.[17] The varying impact attracted inquiry from the scientific community and general  
20 population alike on the potential benefits and costs of the policy of trace and quarantine. [2, 20] From epidemiological  
21 perspective, the usage of trace and quarantine is often viewed as crucial in containing outbreak. While there is a strong  
22 support for usage of trace and quarantine, there is no substantial agreement on the extent to which trace and quarantine  
23 should be employed. On one hand, requiring the entire population to quarantine for weeks at end may effectively  
24 end transmission of a virus but such a policy is untenable as the modern society has complex interdependence, which  
25 require a sufficiently large group of workers to return to workplace. Since not everyone can be quarantined, one may  
26 wonder if everyone except essential workers can be quarantined; such a policy, while feasible, has high cost as prolonged  
27 periods of quarantine is associated with increase in violence, poor mental and physical health in addition to significant  
28 loss in the productivity.[16, 28, 29] Consequently, since the early days of Covid-19 pandemic, the policy of trace and  
29 quarantine was met with polarized reception. On one hand, the proponents of trace and quarantine touted its ability to  
30 quickly identify and isolate potentially infected people, and thereby allowing to manage outbreak. On the other hand,  
31 the opponents of trace and quarantine resisted a broad surveillance of citizens by the governments as it enhanced the  
32 risk of leakage of sensitive private data. [10, 22] Since the trace and quarantine policies adopted political symbolisms,  
33 and consequently, the opposing viewpoints increasingly became polarized, and consequently, one often tends to be  
34 either pro- or anti-trace and quarantine. Since increased polarization left little room for nuance, the implementation  
35 details of trace and quarantine has not attracted detailed scientific scrutiny.

36 The primary contribution of this paper is a detailed methodological analysis of benefits of different models of trace  
37 and quarantine. In particular, we employ a contact graph wherein every node corresponds to a person, and two nodes  
38 are connected if they had direct contact with each other. The representation as a graph allows for a natural formalization  
39 of a given trace and quarantine policy wherein a policy enforces degree  $d$  of quarantine if all the nodes within  $d$  hops  
40 of node  $U$  are required to quarantine if  $u$  is confirmed to be covid positive. Since the connectivity characteristics differ  
41 across different societies, we employ different models of the graphs. We focus on analysis of the cost of a policy with  
42 respect to the different degrees of quarantine wherein the cost is expressed as a linear combination of cumulative  
43 person-hours spent as symptomatic infected, asymptomatic infected, and quarantined. Our analysis results into a  
44 surprising conclusion: the cost is not necessarily monotone with respect to the degree of quarantine, i.e., depending on  
45 the underlying structure of the contact graph, higher degree of quarantine may lead to higher cost. In fact, we observe  
46 that even cumulative quarantine time is non monotonic with respect to degree of quarantine.

47 Our analysis indicates that the implementation of trace and quarantine requires a nuanced analysis, and the  
48 governments must curb the urge to adopt simplistic policy. In particular, the optimal degree of quarantine is closely  
49 dependent on the underlying social structure of a given society as well as the characteristics of the disease. In addition

50 to the detailed analysis, we also release the associated software system via web (<https://contact-tracing.herokuapp.com/>)  
51 with an intuitive interface that allows experts to perform such studies for different underlying networks, infection  
52 transmissions, and different cost functions.

53 The rest of the article is organized as follows: We first provide background to the underlying contact graph structure,  
54 infection transmission models, and trace and quarantine strategies in Section 2. We then present, in Section 3, a  
55 discussion of the simulation study and analyze a paradoxical behavior with respect to cumulative quarantine time.  
56 We then analyze, in Section 4, the optimal degree of quarantine with respect to different costs. We finally conclude in  
57 Section 5.

## 58 2 DESCRIPTION OF OUR MODEL AND PARAMETERS

### 59 2.1 Ground networks

60 In this article, we consider different models for static networks of people defined by physical proximity. A pair of two  
61 persons would be viewed as neighbors in these networks if they spend sufficient time in close physical proximity so  
62 that infection can directly transmit from one to the other. Suppose there are  $n$  people in the network. We will consider  
63 different network topology, ranging from two-dimensional grids to Erdos-Renyi random graphs and hybrid graphs  
64 modelled on real world countries. In case of the grid, there is no other network parameter, whereas the random graph  
65 models would have additional parameters, e.g. the connectivity parameter  $p$  for Erdős-Rényi (ER) random graph  $G(n,p)$   
66 on  $n$  nodes.

### 67 2.2 Infection spreading mechanism

68 In the literature, several agent-based stochastic models have been proposed and studied to capture different aspects of  
69 the infection spreading mechanism. Examples include (i) SI (susceptible-infected), (ii) SIR (susceptible-infected-removed),  
70 (iii) SIS (susceptible-infected-susceptible), (iv) SIRS (susceptible-infected-removed-susceptible) epidemic models and  
71 their variants [30]. In case of Covid, it was noticed that a significant portion of the infected people do not show any  
72 symptoms[32], and after recovering from the infection individuals retain immunity for some time (the immunity is not  
73 permanent [12]). Keeping these features in mind, we would consider a variant of the SIR model, which is referred to  
74 as the SEYAR model [11]. In this model, each person has one of the five possible states – susceptible (S), exposed (E),  
75 symptomatic infected (Y), asymptomatic infected (A), and removed (R). An individual moves from S compartment to  
76 E compartment at rate  $\beta$  times the number of Y and A neighbors, and from E compartment to either Y compartment  
77 (with probability  $p$ ) or A compartment (with probability  $q = 1 - p$ ). Finally, people move from Y or A compartment to R  
78 compartment at rate  $\gamma_Y$  and  $\gamma_A$  respectively. We modify this model to incorporate the disease progression patterns  
79 which have been observed specifically in the case of Covid-19. Instead of using fixed rates for the transitions between  
80 different states (e.g., from E (resp. E, Y, A) to Y (resp. A, R, R)), we use random samples from the respective distributions  
81 (see the following table), which have been empirically shown to fit the corresponding real world observed data [3, 21],  
82 for the holding times at states E, Y, and A. Furthermore the model considers that 30% of all infections are asymptomatic  
83 which is an aggregation from many studies[23]. The rates of infection of an asymptomatic individual has been set to  
84 80% of that of a symptomatic individual due to a lack of consensus of studies for the same.

Period or Transition	Compartment	Distribution
Incubation period	Exposed (E)	Lognormal with mu 1.63 and sigma 0.5 [21]
Symptomatic duration	Symptomatic (Y)	Normal distribution with mean 13.4 days[3] and variance of 3 days
Asymptomatic duration	Asymptomatic (A)	Uniform distribution between 6.5 and 9.5 days[3]

### 86 2.3 Trace and Quarantine Strategies

87 In the trace and quarantine policy, if a person is detected to have the infection, then that person, his/her recent contacts,  
 88 and their subsequent contacts etc. are immediately quarantined. The stringency of the policy depends on how many  
 89 levels of contacts one traces. In the

- 90 • zero degree policy, neither tracing nor quarantining anyone occurs.
- 91 • first degree policy, people who are symptomatic or tested positive are quarantined.
- 92 •  $k$ -degree policy (for any  $k \geq 2$ ), people who would be quarantined according to the  $(k-1)$ -degree policy as well  
 93 as all of their neighbors are quarantined.

94 One can extend the definition of the degree of contact tracing to any non-integer positive number  $k$  by adopting the  
 95  $[k]$  policy, and additionally quarantining each of the persons, whose graph distance from the originally detected person  
 96 is  $k+1$ , with probability  $k - [k]$ . Note that in the real world each level of tracing has a time delay as the agents in  
 97 question have to be contacted and appropriate actions have to follow. Thus an additional parameter representing delay  
 98 in subsequent tracing called 'tracing delay' has been included in the model. Additionally, 'quarantine time' has been  
 99 set to 14 days unless otherwise stated and refers to the duration of quarantine after being identified in the trace and  
 100 quarantine strategy.

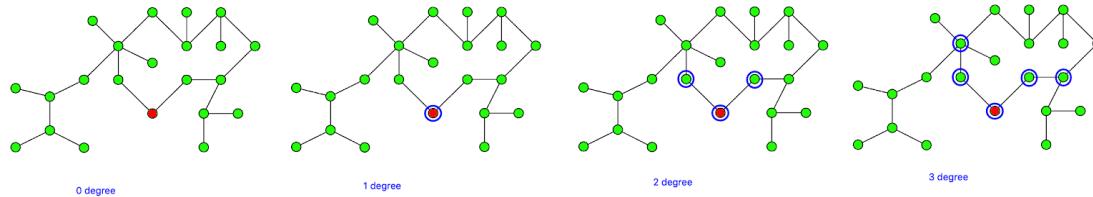


Fig. 1. Different degrees of quarantine where the nodes represent people and the edge between two nodes represents contact between the corresponding two people. A node is red if the corresponding person has been identified to be infected, and a node is blue encircled if the corresponding person is quarantined.

### 101 2.4 Simulation Parameters

102 We consider a finite horizon with a fixed time frame of 100 days. Furthermore to ensure verifiable results every  
 103 simulation has used a fixed random seed. The logs of each simulation have been stored and can exactly reproduce each  
 104 simulation and corresponding figures shown in the paper. Throughout this paper, in order to reduce variance in this  
 105 complex non-deterministic system with largely inherent stochasticity or randomness, all shown results are averaged

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106 over multiple instances of the simulation. The number of instances were determined by the convergence of the final  
 107 result. Although variance can be introduced as a risk metric, this is not in the scope of this paper.

108 **3 SIMULATION STUDY**

109 We empirically study SEYAR disease dynamics on the agent network and compare different degrees of the trace and  
 110 quarantine strategy<sup>1</sup>. This paper deals with 3 types of graphs namely Erdos-Renyi random graph, a structured 2D grid  
 111 graph of degree 4, and a hybrid country graph inspired by real countries.

112 **3.1 Understanding the simulation**

113 We consider a SEYAR model with the chance of an Exposed becoming Asymptomatic being 3 times higher than  
 114 becoming Symptomatic. The underlying agent network is represented by a Erdos-Renyi graph with 5000 persons and a  
 115 0.001 probability of an edge(Bernoulli,iid) between any two persons. The average degree is 5. This simulation runs  
 116 through for 100 days or time-steps. We present the simulation of perfect contact tracing with no error while applying  
 117 the strategies.

118 We choose a closed world with the above priors. Each simulation starts with a small number of initial exposed agents  
 119 after which there is no interference from outside the system. Each time step the people run through the SEYAR model  
 120 and accordingly change states. For each strategy the simulations are averaged multiple times to reduce variance and  
 121 noise.

122 The figure 2 shows the comparison between the strategies with different degrees of quarantine. The three bars  
 123 in the histogram refer to the cumulative time of all agents being Symptomatic(Blue), Asymptomatic(Orange) and  
 124 Quarantined(Green). Note that an agent cannot be both Symptomatic and Asymptomatic at the same time but can be in  
 125 one of those states along with being quarantined at a given time step.

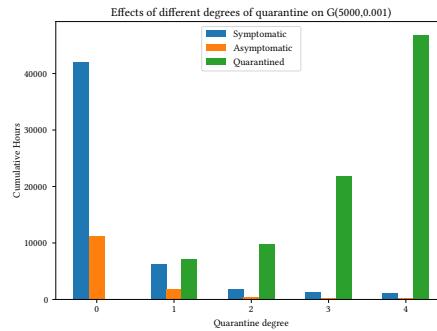


Fig. 2. Comparison of different degrees of quarantining based on the cumulative time spent by all the nodes of a  $G(5000,0.001)$  Erdos-Renyi random graph in different states. There is a trace delay of 2 days and a quarantine time of 14 days. It is clearly seen that increasing the degree of quarantine results in an improved control over the spread of the disease as seen by the cumulative infection.

126 As expected we see that increasing the degree of quarantine naturally increases the cumulative quarantine hours  
 127 as we are quarantining more and more people. This strategy naturally results in lower disease spread resulting in  
 128 lower total cumulative Symptomatic and Asymptomatic time. It is a standard phenomenon for any disease that

<sup>1</sup>Our tool is available at <https://contact-tracing.herokuapp.com/>

129 spreads through exposure to infected people such that it occurs irrespective of the disease dynamics. One can also  
 130 notice a significant improvement in the first degree of quarantine and marginal improvement thereafter. This result  
 131 is related to the underlying structure or the graph in conjunction with the disease dynamics and shall be explored further.  
 132

### 133 3.2 Cumulative quarantine paradox

134 As seen in figure 2 it is intuitively clear at to why the cumulative quarantine time increase with increase in quarantine  
 135 degree. This effect can be attributed to the simple fact that we have more agents under our purview. But the counter-  
 136 intuitive fact is that under certain ranges of parameters which include the edge probability in an Erdos-Renyi graph  
 137 or the underlying disease dynamics(rate of infection, rate of recovery) we see that the cumulative quarantine time is  
 138 non-monotonic.

139 This phenomenon illustrated in figure 3 can be explained using the following mathematical reasoning. If a higher  
 140 degree of quarantining policy is adopted, then, on the one hand, there would be the fewer total number of infections  
 141 which in turn reduces the total quarantine hours, but on the other hand, more people would be quarantined per  
 142 infection detection which would increase the total quarantine time. The argument can be made more precise using a  
 143 "coupling argument" [18]. Let  $\xi_t^k$  (resp.  $\zeta_t^k$ ) denotes the set of infected (resp. quarantined) people at time  $t$  when degree  
 144  $k$  quarantine policy is adopted. For any set of values of the SEYAR model parameters and  $k < l$ , the infection and  
 145 contact tracing processes corresponding to degree  $k$  and  $l$  quarantine policy can be coupled so that  $\xi_t^l \subset \xi_t^k$  for all  $t$ .  
 146 Moreover, if  $A_t := \xi_t^l \setminus \xi_t^k$  and  $B_t := \zeta_t^k \setminus \xi_t^l$ , then both  $A_t$  and  $B_t$  are possibly nonempty.  $A_t$  consists of people belonging  
 147 to  $\xi_t^k \setminus \xi_t^l$  who would be quarantined under the degree  $l$  quarantine policy. On the other hand,  $B_t$  consists of people  
 148 who would be quarantined in the degree  $k$  quarantine policy and whose infection trail remains within  $\cup_{s < t} \xi_s^k \setminus \xi_s^l$ . The  
 149 SEYAR model parameters and the parameters of the underlying graph determines whether the expected values  $E(|A_t|)$   
 150 and  $E(|B_t|)$  satisfy  $E(|A_t|) \leq E(|B_t|)$  or not, which in turn determines whether  $E(|\zeta_t^l|) \leq E(|\zeta_t^k|)$  or not.

151 Thus, the cumulative quarantine time (green bar) is expected to be decreasing (resp. increasing) as a function of the  
 152 quarantine degree when the quarantine degree is small (resp. large). The minima of the curve may occur before the first  
 degree as seen in Figure 2 or it may occur at a higher degree as noticeable in the plots of figure 3.

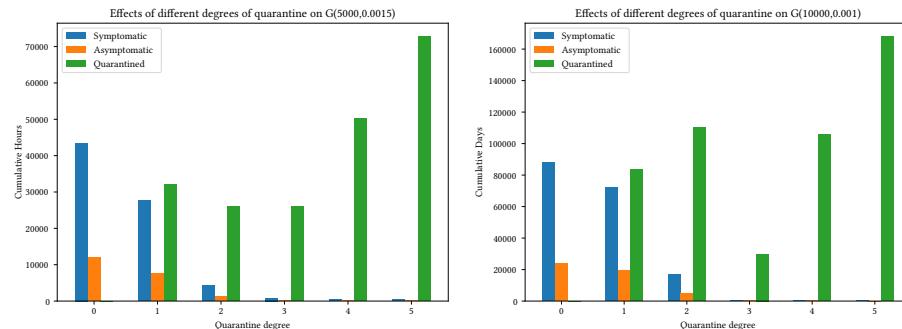


Fig. 3. Both plots on  $G(5000,0.0015)$  and  $G(10000,0.001)$  show the non-monotonic behaviour of cumulative quarantine time. This figure shows that it is not a pure artifact of a random run on a specific graph as these results have been averaged over multiple individual simulations. The trace delay is 1 day and quarantine time 14 days.

154 **3.3 A more practical scenario**

155 We introduce a hybrid graph modelled on the family structure of respective countries. A family is considered as a  
 156 completely connected network and is modelled as a clique. Each agent is assigned a clique based on the distribution  
 157 of family sizes in the country (Figure 4). To this we append an underlying Erdos-Renyi random graph connecting the  
 agents.

Country\Family Size	1	2-3	4-5	6+
Nederland	35%	46%	18%	1%
USA	27%	49%	20%	5%
India	4%	24%	42%	31%
Afghanistan	0%	6%	17%	77%

Fig. 4. The distribution of family sizes in each country. united nations The orange highlight shows the distribution of over 80% of the population in the respective country. Notice that Netherlands (country with smallest average family size) has a significantly different structure from Afghanistan (country with largest average family size).

158  
 159 The family structure and rate of interaction in a region heavily impact the spread of the disease. [19] This interaction  
 160 results in varying effects of the same strategies across different regions. In figure 5 note the significant variation in  
 161 effects of strategies from top to bottom and also left to right. This plot shows us that average interaction and family size  
 162 play an important role in determining the effect of the strategy. One should notice that the weather, diet, health and  
 163 infrastructure of Netherlands and Afghanistan are very different which will even further vary the outcomes of disease  
 164 spread. The bottom right plot shows us that there is no significant effect in the first degree quarantine while the top  
 165 left shows us that the first degree quarantine has the most effective increase in controlling spread. Furthermore the  
 166 monotonicity of cumulative quarantine hours varies drastically across all plots.

167 **3.4 Other observed behaviours**

168 Sparseness of graph in conjunction with rate of recovery drastically determine how many people get infected over  
 169 the course of the epidemic. [6] This effect is due to a high rate of recovery, which essentially results in cutting off of  
 170 sections of sparse graphs resulting in a local notion of herd immunity. A classic example is of a village where only the  
 171 shopkeeper interacts with the outside world. If the shopkeeper recovers and becomes immune before transmitting the  
 172 disease into the village the only path of the disease into the village is now blocked (assuming no carriers and that the  
 173 disease spreads only by contact). Furthermore the rate of infection determines how fast the disease can spread while  
 174 the ratio of symptomatic to asymptomatic shows the extent to which we can identify a disease without testing. All of  
 175 this further begs the questions regarding the best course of action. It is clear that every region is unique in its own way  
 176 and must take a decision on which strategy to implement. This observation calls for an optimal degree of trace and  
 177 quarantine which is discussed in the following section.

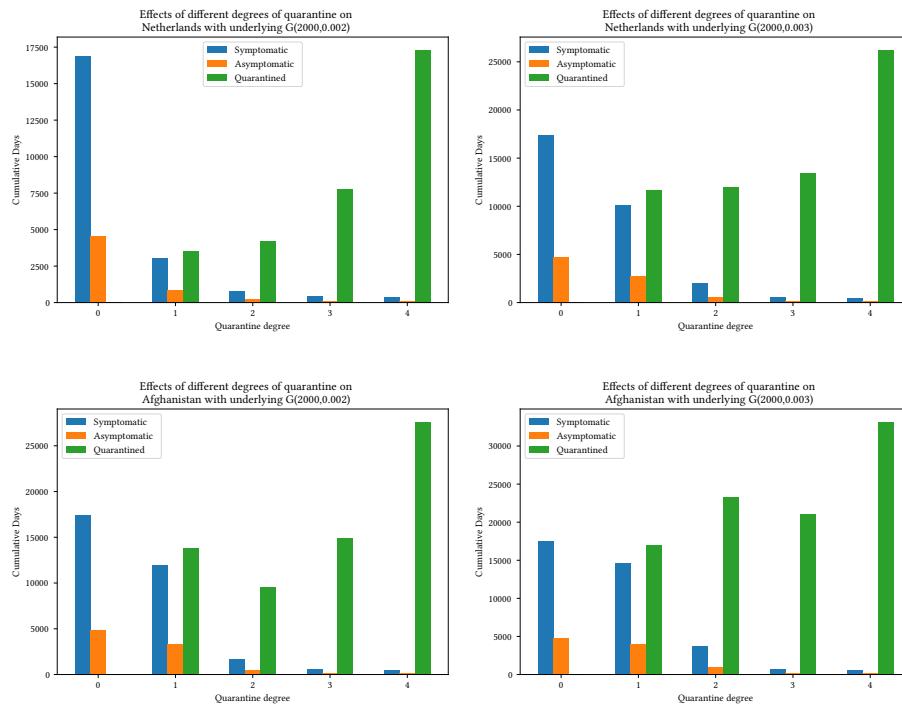


Fig. 5. Comparing strategies of different quarantine across interaction networks modelled on different countries.

The 4 plots are put in the following order for easy and quick visual comparison. The top two plots consider a graph structure modeled on the family size distribution of Netherlands. The bottom two consider a graph structure modeled on the family size distribution of Afghanistan. Both plots on the left assume more interactions outside the family on average ( $p = 0.003$  for the underlying ER graph). Both plots on the right assume sparser interactions outside the family ( $p = 0.002$  for the underlying ER graph). All plots have been averaged over multiple individual simulations to reduce variance and noise. The trace delay is 1 day and quarantine time 14 days.

## 178 4 OPTIMAL DEGREE

### 179 4.1 Policies are not free

180 Every quarantine policy enacted in a region would be associated with a cost to the overall economy of that region which  
 181 needs to be considered before deciding whether the policy should be adopted or not. Broadly speaking, there can be two  
 182 kinds of costs in this context, namely "economic costs" and "health costs." If a person is quarantined, then he/she would  
 183 not be able to take part in the economic activities and contribute to the economy during the quarantine period. Moreover,  
 184 the policymaker may need to arrange for food, other subsistence, medical supplies, etc. for the quarantined persons.  
 185 These constitute the economic cost. The economic cost associated with a person would depend on the employment  
 186 status, socio-economic status, health status, etc. of that person. The health cost associated with a quarantine policy  
 187 stems from the associated rates at which critical patients (belonging to different age and comorbidity groups) requiring  
 188 hospitalization show up, rates at which the necessary equipment and medical supplies for the treatment of infected  
 189 patients would be needed, etc.

190     Although, in theory, any level of quarantine can be considered, all policies may not be feasible to enact in a given  
191     region due to a lack of necessary infrastructure and capability. Keeping such practical concerns in mind, we need to  
192     consider only the feasible policies to choose from. In many cases, the economic costs and health costs are not readily  
193     available. Depending on the proportion of different contributing factors, the cost structure can vary from place to  
194     place, and it needs to be estimated carefully. The accuracy of the overall estimation procedure would depend on the  
195     noise present in the measurements of the predictor variables, the kind of relationship (linear or nonlinear) between  
196     the overall cost and its components, and the noise involved in the execution of the contact tracing procedure. In this  
197     paper, we would not address the estimation problem; rather, we demonstrate the consequence of a particular kind  
198     of cost structure. The overall cost is a linear combination of the components. Similar behavior is expected for other  
199     relationships. Other contributors to the overall cost include human resources and logistics for carrying out the contact  
200     tracing procedure, but these factors would not be considered here, as they do not seem to be a major factor.

#### 201     **4.2 Cost Structure**

202     For every policy the community seeks to implement, there is an associated cost borne by the community. Here, cost  
203     does not imply the mere monetary expense but a total encoding of all effects. This cost structure encodes the priorities,  
204     expenses and constraints of a community.<sup>[4]</sup>

205

- 206     • **Priorities** : Every community is unique in their needs, vulnerabilities and abilities which determine their priorities.  
207     Quarantine for an affluent community with savings is not as harsh as quarantine of a less fortunate community  
208     that lives on a day to day wage. Furthermore communities differ in inherent strengths and weaknesses. For  
209     example a nursing home is much more likely to result in deaths as compared to an undergrad college with the  
210     same of number of cases.
- 211     • **Expenses** : The expenses associated with a community depends on many other factors including the demographic  
212     composition, socio-economic factors, healthcare infrastructure, the level of awareness, perception, and sensitivity  
213     of people. At a basic level the GDP, technological progress, infrastructure and resources of a country determine  
214     various expenses. Even at a local level expenses can vary across neighbourhoods due to availability of labour,  
215     demand and supply of resources and transport. An example is that of transport, tracing personnel, quarantine  
216     and machine expenses.
- 217     • **Constraints** : A variety of factors like Infrastructure, Availability of resources, Demand and Supply, Government  
218     Regulations constrain the possible policies a community can implement. Constraints could include a minimum  
219     number of infections, deaths, quarantine days and could also include bounds on the total number of false  
220     quarantine.

221     We consider a cost structure that is composed of the following four components:

- 222     (1) cost for quarantining people ( $C_1$ ) – this cost stems from the fact people will not be able to take part in economic  
223     activities involving physical interactions. So, financial support need to be arranged for such people.
- 224     (2) cost incurred by the asymptomatic infected people ( $C_2$ ) – this cost stems from the fact that the asymptomatic  
225     infected people spread infection at relatively faster rate to their susceptible neighbors which comes with health  
226     cost dues to hospitalizations, health hazards, and fatalities.

227 (3) cost incurred by the symptomatic infected people ( $C_3$ ) – this cost stems from the fact that the symptomatic  
 228 infected people, who are not quarantined, spread infection at relatively slower rate to their susceptible neighbors  
 229 which comes with health cost dues to hospitalizations, health hazards, and fatalities.

230 Another main component is the fixed costs that includes setting up the tracing and identification system and  
 231 other processes like information dissemination. Since it is fixed, we formalise our cost structure with only the three  
 232 components as a tuple ( $C_1, C_2, C_3$ ).

233 **4.3 Cost Function**

234 Given a policy, the cost function returns the total cost borne by the community, which is determined by the cost  
 235 structure.

236 We consider the cost function as the linear combination of the cost components.

$$C = n_1 C_1 + n_2 C_2 + n_3 C_3 \quad (1)$$

237 Where,  $n_1$ ,  $n_2$  and  $n_3$  are the total number of quarantined days, asymptomatic infected days, symptomatic infected  
 238 days and infections respectively. With a semblance of sanity we can assume certain conditions on  $n_1$ ,  $n_2$  and  $n_3$ . Clearly  
 239 they are non-negative as no community will want to increase any of the above components. Also as quarantine  
 240 is preferred over being infected and furthermore a symptomatic person will bear higher cost than an asymptomatic  
 241 person we can naturally incite the condition  $n_1 < n_2 < n_3$ . Additional constraints like an significantly higher cost for  
 242 infected over quarantine can be placed which shall be discussed in future works. Furthermore the logistic cost of tracing  
 243 is negligible with today's technology and can be subsumed in the cost for quarantine itself.

244  
 245 We have considered linear cost components but this may be appropriately adjusted to capture the community's utility.  
 246 For example a community which shuns excessive deaths could penalise the cost function with a quadratic component in  
 247 the number of deaths. Note that one can easily extend this cost to encode the cost of death which occurs as a proportion  
 248 of the total infected population. But constraints like hospital space and medication might affect this resulting in a non  
 249 linear piece-wise cost function. The simplest linear cost function is enough to show the non-monotonic nature of cost  
 250 with respect to degree of quarantine. A more complex function will further exacerbate these observations.

251  
 252 **Goal** : Find the optimal degree of trace and quarantine that minimizes the cost function. Given the parameters of the  
 253 underlying population network, infection spreading process, and the different kinds of costs, we want to obtain the  
 254 value of  $k$  (the degree of contact tracing) for which the combined cost would be minimized.

255 **4.4 Comparing Cost Structures**

256 As discussed above for each region the cost structure varies vastly. We consider  $G(2000, 0.006)$ , the Erdos-Renyi random  
 257 graph on 2000 nodes, as the underlying agent network. The cost structure that we use considers of the following. A unit  
 258 time of quarantined, asymptomatic, and symptomatic period spent by one person costs 1, 2, and 3 units respectively.  
 259 We obtain the cumulative cost for all the agents of the underlying network for different degrees of quarantining. See  
 260 Figure 6(b) for the comparison of cumulative costs under different quarantine strategies.

261 We see that the cost of quarantine is not monotonic. Instead we see that the cumulative cost minimizes at quarantine-  
 262 degree 3. If one would change the cost structure, then the optimal quarantine-degree would change accordingly. Thus,

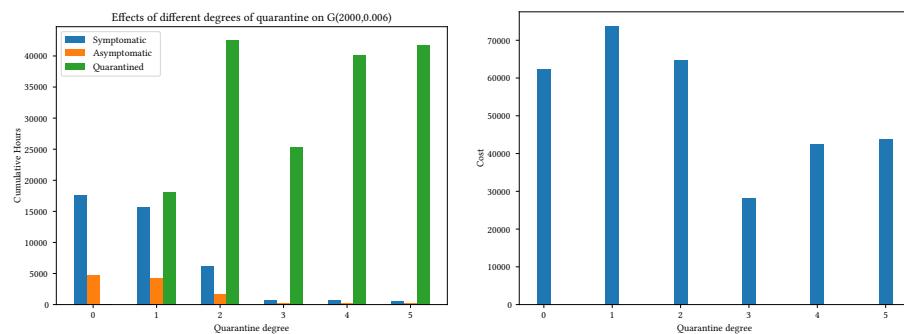


Fig. 6. Left: Comparison of different degrees of quarantining based on the cumulative time spent by all the nodes of an ER random graph in different states. Right: Comparison of different degrees of quarantining based on the cost structure (1,2,3). The trace delay is 1 day and quarantine time 14 days.

263 the best quarantine strategy depends on both of the factors: (a) relative costs of being symptomatic and asymptomatic  
 264 relative to the quarantine-cost, and (b) the underlying structure of the graph.

265

266 Next we consider the  $40 \times 40$  Grid graph on 1600 nodes, as the underlying agent network. The cost structure that we  
 267 use considers of the following. A unit time of quarantined, asymptomatic, and symptomatic period spent by one person  
 268 costs 1, 2, and 3 units respectively. This comparison has been shown in figure 7.

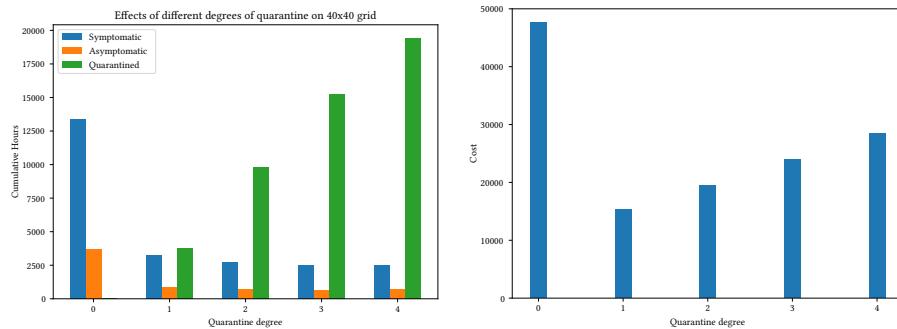


Fig. 7. Left (6a): Comparison of different degrees of quarantining based on the cumulative time spent by all the nodes of a  $40 \times 40$  Grid graph in different states. Right (6b): Comparison of different degrees of quarantining based on the corresponding cost. The trace delay is 2 days and quarantine time 14 days.

269 We observed that the non-monotonic cost structure is not restricted to random graphs. We see that degree 1 strategy  
 270 is optimal. The optimal strategy changes according to associated costs. This analysis shows that the phenomenon is  
 271 not an innate quality of certain kinds of graphs but instead a result of the strategy under the dynamics of an epidemic  
 272 spreading along the agent network.

273

274 It is also possible that doing neither contact-tracing nor quarantine is the optimal strategy. Effectively a 0 degree  
 275 trace and quarantine strategy may be treated as a baseline. As seen in the bottom two plots of figure 8 we see that the 0  
 276 degree strategy can be optimal as seen with cost structure (1,2,5). Though counter-intuitive we have considered multiple  
 277 cost structures and shown how the optimal degree can vary. This phenomenon can be attributed to the fact that 1  
 278 degree quarantine does not show significant improvement, while later degrees show great improvement in disease  
 279 control but a high cumulative quarantine increases the cost. But on further inspection we see that based on the structure  
 280 we see how the monotonicity of the cost changes with trace delay and structure of graph. This is most evident with the  
 281 (1,2,10) cost structure which drastically changes shape across all plots. Additionally observe how the optimal degree  
 282 varies as we change the cost structure, graph structure and delay in tracing.

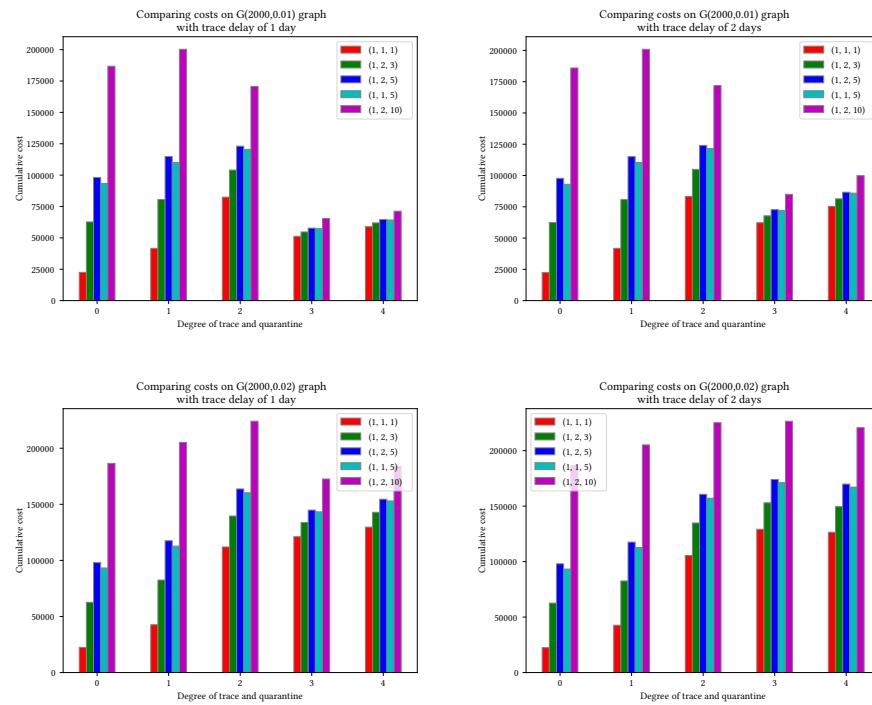


Fig. 8. Left: Comparison of different degrees of quarantining based across cost structures, trace delay and connectivity parameter  $p$ . The left plots assume a trace delay of 1 day while the right two plots assume a trace delay of 2 days. The top plots are run on  $G(2000,0.01)$  while the bottom two are on  $G(2000,0.02)$ . The colors from Red, Green, Blue, Cyan and Violet represent the cost structures  $(1,1,1), (1,2,3), (1,2,5), (1,1,5)$  and  $(1,2,10)$  respectively.

283 **4.5 Error in Tracing**

284 We have considered a wide variety of factors in our attempt at modelling 'trace and quarantine' strategies of different  
 285 degree's across structural variations in the underlying agent network. We shall now explore a natural extension to the  
 286 current model.

287 Contact tracing is never perfect.[14, 15, 17] A wide variety of factors ranging from lack of coordination among the  
 288 various hierarchies of policy making, delay in quick tracing of contacts, lack of cooperation from the public and normal  
 289 human error it is nearly impossible to find every contact. We define error in tracing as follows : a  $k\%$  error corresponds  
 290 to finding a contact with probability  $1 - k/100$ . This error model applies for finding contacts at any degree. This error  
 291 is further magnified as we propagate to the next level of contacts . As seen in figure 9 change in error results in an  
 292 unpredictable change in the final cost and thus optimal degree of trace and quarantine strategy.

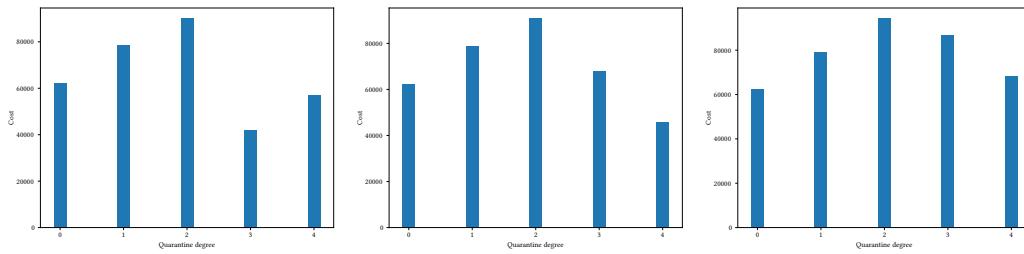


Fig. 9. We consider a SEYAR model on  $G(2000, 0.007)$  ER graph. From Left to Right the plots represent error 0%, 20%, and 40% with optimal degree 3, 4, and 0 respectively. All 3 plots consider the same dynamics with the same random seed and was averaged over multiple simulations. The cost structure is 1, 2, and 3 per unit time of quarantined, asymptomatic, and symptomatic respectively.

#### 293 4.6 Optimal Region

294 We see the formation of optimal regions based on the cost structure for Erdos-Renyi graphs. Although dependent on  
 295 the disease dynamics and graph parameters we can find the optimal degree.

296 In figure 10 we can see the optimal degree under different cost structures. The plots show that based on the associated  
 297 costs either degree 0 or degree 3 is optimal. Thus under the certain cost structures it is optimal to do no quarantining at  
 298 all. We can clearly see the shift in quarantine degree as we change the associated costs. There is thus an optimal degree  
 299 which varies largely with the cost structure. Furthermore the difference between the plots show the large impact the  
 300 underlying structure has on the final cost and thus the optimal strategy.

#### 301 5 DISCUSSION

302 In this paper, we have analyzed the effects of different degrees of quarantine policy for a region on the total quarantine  
 303 time and on the associated cost for the economy of that region. We have considered the SEYAR model the infection  
 304 spreading mechanism, and used different (random and deterministic) graphs as models for physical proximity net-  
 305 work. We have demonstrated that the optimal (or near-optimal) quarantine policy is far from any obvious choice. It  
 306 depends on the parameters of the disease spreading mechanism, the topology of the underlying proximity network, and  
 307 the cost structure in a nontrivial way. The cost structure associated with a region in turn would depend on many  
 308 other factors including the demographic composition, socio-economic factors, healthcare infrastructure, the level of  
 309 awareness, perception, and sensitivity of people, measures taken by law enforcing agencies. So, any adhoc choice  
 310 of quarantine policy may inflict unnecessary burden on the economy. Our framework helps to find out the optimal  
 311 (or any near-optimal) policy once the associated cost structure and disease spreading mechanism are understood.  
 312 The framework also allows to check how robust the optimal policy is by perturbing the influencing factors in any

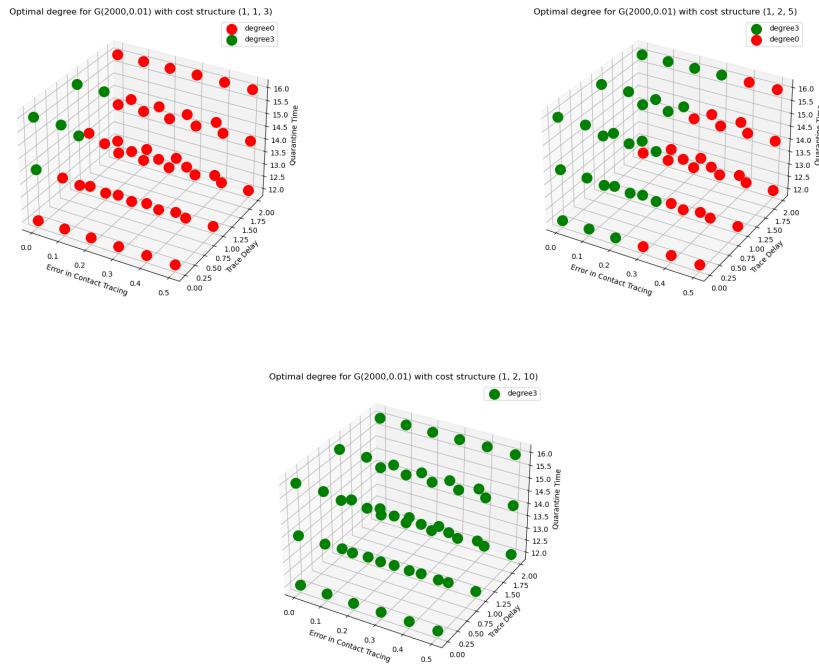


Fig. 10. Optimal Quarantine degree given error in tracing, trace delay and duration of quarantine.

Method: We consider a SEYAR model on a  $G(2000,0.01)$  graph. We run the simulations on respective Erdos-Renyi graphs with different cost structures varying from  $(1,1,3)$ ,  $(1,2,5)$  and  $(1,2,10)$  from left to right. We find the optimal degree out of  $0,1,2$  and  $3$  based on the minimum cost averaged over multiple simulations. We vary the error in tracing, trace delay and duration of quarantine to get the parameters for each point.

313 direction and comparing the resulting optimal degree of quarantining. The framework can also incorporate any available  
 314 information about the proximity network, disease spreading mechanism, or the cost structure into the optimal policy  
 315 determination procedure. For example, if the physical proximity network for a region can be estimated in a better  
 316 way using the relevant transportation data, movement data obtained from cell phone locations of individuals, or  
 317 aggregated visit data, the our analysis can be conducted on the resulting deterministic proximity network. Instead,  
 318 if some characteristics (e.g. degree distribution) about the proximity network is known only, then we can choose a  
 319 random graph having those characteristics and conduct our analysis on that. In conclusion, we present a flexible and  
 320 useful framework for obtaining optimal (and near-optimal) quarantine policy based on information about the proximity  
 321 network, disease spreading mechanism, and cost structure. The policymaker needs to understand these components  
 322 better in order to arrive at any rational conclusion about whether to adopt any quarantine policy or not.

323 Our work opens up several interesting avenues of future work; we sketch out three directions of interest:

324 **Compliance** Human behaviour is erratic and unpredictable. Furthermore in challenging times, people tend to  
 325 function irrationally.[1, 25] Thus compliance to quarantine, test or even name contacts is not a task for enforcers  
 326 and must be accounted for by policymakers.

327 **Heterogeneous population** Humans are heterogeneous, even identical twins vary in multiple attributes. Demog-  
 328 raphy(Age, Gender, Profession) plays a crucial role in interaction and risk measure of a person. Furthermore  
 329 genetic markers and innate factors like the blood group or HLA type may determine the susceptibility of a person  
 330 to Covid-19 and also the chances of recovery.[24]

331 **Other policies** Trace and quarantine is not a stand alone policy. Other interventions and strategies like testing,  
 332 vaccination, curfew, and lockdown affect the result of any other policy. It is imperative to consider the larger  
 333 amalgamated picture before taking any decision.

334 **6 ACKNOWLEDGEMENT**

335 In mid-March of 2020, with the aim of combating Covid-19, approximately 150 members from around the world  
 336 organically converged to form the "cure COVID-19 for Ever and for All" (RxCovea:<https://rxcovea.org/>) Group, a rigorous  
 337 community of scientists, clinicians, AI-specialists, mathematical and computational/data modelists, pharmaceutical,  
 338 public and digital health intelligence representatives from multiple institutions, countries and scientific training. Within  
 339 the network, self-organized task forces continue to conduct core projects, structured around hypotheses and minimal  
 340 viable products (MVP's), mentored and examined by experienced senior members. We thank RxCovea for useful  
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342 **REFERENCES**

- 343 [1] Alisha Arora, Amrit Kumar Jha, Priya Alat, and Sitanshu Sekhar Das. 2020. Understanding coronaphobia. *Asian Journal of Psychiatry* 54 (Dec. 2020),  
 344 102384. <https://doi.org/10.1016/j.ajp.2020.102384>
- 345 [2] Rinad S. Beidas, Alison M. Buttenheim, Rachel Feuerstein-Simon, Austin S. Kilaru, David A. Asch, Kevin G. Volpp, Hannah G. Lawman, and  
 346 Carolyn C. Cannuscio. 2020. Optimizing and Implementing Contact Tracing through Behavioral Economics. *Njm Catalyst Innovations in Care  
 347 Delivery* (23 Jun 2020), 10.1056/CAT.20.0317. <https://doi.org/10.1056/CAT.20.0317> PMC7371277[pmcid].
- 348 [3] Andrew William Byrne, David McEvoy, Aine B Collins, Kevin Hunt, Miriam Casey, Ann Barber, Francis Butler, John Griffin, Elizabeth A Lane,  
 349 Conor McAlloon, Kirsty O'Brien, Patrick Wall, Kieran A Walsh, and Simon J More. 2020. Inferred duration of infectious period of SARS-CoV-2:  
 350 rapid scoping review and analysis of available evidence for asymptomatic and symptomatic COVID-19 cases. *BMJ Open* 10, 8 (2020). <https://doi.org/10.1136/bmjopen-2020-039856> arXiv:<https://bmjopen.bmj.com/content/10/8/e039856.full.pdf>
- 351 [4] Surya Dheeshjith, Inavamsi Enaganti, and Bud Mishra. 2021. Testing the efficacy of epidemic testing. arXiv:2109.07580 [physics.soc-ph]
- 352 [5] Todd Pollack et al. [n.d.]. Emerging COVID-19 success story: Vietnam's commitment to containment. <https://ourworldindata.org/covid-exemplar-vietnam>
- 353 [6] Matthew J Ferrari, Shweta Bansal, Lauren A Meyers, and Ottar N Bjørnstad. 2006. Network frailty and the geometry of herd immunity. *Proceedings  
 356 of the Royal Society B: Biological Sciences* 273, 1602 (Aug. 2006), 2743–2748. <https://doi.org/10.1098/rspb.2006.3636>
- 357 [7] Centers for Disease Control and USA Prevention. [n.d.]. COVID-19: When to Quarantine. <https://www.cdc.gov/coronavirus/2019-ncov/if-you-are-sick/quarantine.html>
- 358 [8] Centers for Disease Control and USA Prevention. [n.d.]. Older Adults and COVID-19. <https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/older-adults.html>
- 359 [9] International Monetary Fund. [n.d.]. Policy Responses to COVID19. <https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19>
- 360 [10] Michelle Hampson. [n.d.]. Why Aren't COVID Tracing Apps More Widely Used? <https://spectrum.ieee.org/tech-talk/computing/software/why-arent-covid-tracing-apps-more-widely-used>
- 361 [11] Herbert W Hethcote. 2000. The mathematics of infectious diseases. *SIAM review* 42, 4 (2000), 599–653.
- 362 [12] Akiko Iwasaki. 2021. What reinfections mean for COVID-19. *The Lancet Infectious Diseases* 21, 1 (Jan. 2021), 3–5. [https://doi.org/10.1016/s1473-3099\(20\)30783-0](https://doi.org/10.1016/s1473-3099(20)30783-0)
- 363 [13] Home COVID-19 INFORMATION PORTAL Karnataka Government. 2021. COVID-19 Official Memorandum. <https://covid19.karnataka.gov.in/storage/pdf-files/Home%20quarantine%20for%20primary%20contacts.pdf>.
- 364 [14] Thorin Klosowski. 2020. COVID Contact Tracing Apps Are Far From Perfect. <https://www.nytimes.com/wirecutter/blog/covid-contact-tracing-apps/>
- 365 [15] Mirjam E Kretzschmar, Ganna Rozhnova, Martin C J Bootsma, Michiel van Boven, Janneke H H M van de Wijgert, and Marc J M Bonten. [n.d.]. Impact  
 366 of delays on effectiveness of contact tracing strategies for COVID-19: a modelling study. [https://www.thelancet.com/journals/lanpub/article/PIIS2468-2667\(20\)30157-2/fulltext](https://www.thelancet.com/journals/lanpub/article/PIIS2468-2667(20)30157-2/fulltext)

374 [16] Manfred Lenzen, Mengyu Li, Arunima Malik, Francesco Pomponi, Ya-Yen Sun, Thomas Wiedmann, Futu Faturay, Jacob Fry, Blanca Gallego, Arne  
375 Geschke, and et al. [n.d.]. Global socio-economic losses and environmental gains from the Coronavirus pandemic. <https://doi.org/10.1371/journal.pone.0235654>

377 [17] Dyani Lewis. 2020. Why many countries failed at COVID contact-tracing - but some got it right. <https://www.nature.com/articles/d41586-020-03518-4>

378 [18] Torgny Lindvall. 2002. *Lectures on the coupling method*. Courier Corporation.

379 [19] Ira M. Longini and James S. Koopman. 1982. Household and Community Transmission Parameters from Final Distributions of Infections in  
380 Households. *Biometrics* 38, 1 (1982), 115–126. <http://www.jstor.org/stable/2530294>

381 [20] Davin Lunz, Gregory Batt, and Jakob Ruess. 2021. To quarantine, or not to quarantine: A theoretical framework for disease control via contact  
382 tracing. *Epidemics* 34 (March 2021), 100428. <https://doi.org/10.1016/j.epidem.2020.100428>

383 [21] Conor McAlloon, Áine Collins, Kevin Hunt, Ann Barber, Andrew W Byrne, Francis Butler, Miriam Casey, John Griffin, Elizabeth Lane,  
384 David McEvoy, Patrick Wall, Martin Green, Luke O’Grady, and Simon J More. 2020. Incubation period of COVID-19: a rapid sys-  
385 tematic review and meta-analysis of observational research. *BMJ Open* 10, 8 (2020). <https://doi.org/10.1136/bmjopen-2020-039652>  
386 arXiv:<https://bmjopen.bmjjournals.org/content/10/8/e039652.full.pdf>

387 [22] Colleen McClain and Lee Rainie. 2020. The Challenges of Contact Tracing as U.S. Battles COVID-19. <https://www.pewresearch.org/internet/2020/10/30/the-challenges-of-contact-tracing-as-u-s-battles-covid-19/>

388 [23] Moges Agazhe Assemie Daniel Bekele Ketema Belayneh Mengist Bekalu Kassie Tilahun Yemanu Birhan Muluneh Alene, Leltework Yismaw. [n.d.].  
389 Magnitude of asymptomatic COVID-19 cases throughout the course of infection: A systematic review and meta-analysis. <https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0249090>. (Accessed on 11/18/2021).

390 [24] Eduardo Muñiz-Díaz, Jaume Llopis, Rafael Parra, Imma Roig, Gonzalo Ferrer, Joan Grifols, Anna Millán, Gabriela Ene, Laia Ramiro, Laura Maglio,  
391 and et al. 2021. Relationship between the ABO blood group and COVID-19 susceptibility, severity and mortality in two cohorts of patients. *Blood  
392 Transfusion* (Jan. 2021). <https://doi.org/10.2450/2020.0256-20>

393 [25] Chinwe U Nnama-Okechukwu, Ngozi E Chukwu, and Chiamaka N Nkechukwu. [n.d.]. COVID-19 in Nigeria: Knowledge and compliance with  
394 preventive measures. <https://pubmed.ncbi.nlm.nih.gov/32970541/>

395 [26] Blavatnik School of Government. [n.d.]. COVID-19 Government Response Tracker. <https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker>

396 [27] Mary A Shiraef. 2021. With closed borders and travel bans, how COVID-19 changed the way people move around the world-Living News ,  
397 Firstpost. <https://www.firstpost.com/living/with-closed-borders-and-travel-bans-how-covid-19-changed-the-way-people-move-around-the-world-9449641.html>

398 [28] Judit Simon, Timea M. Helter, Ross G. White, Catharina van der Boor, and Agata Łaszecka. 2021. Impacts of the Covid-19 lockdown and relevant  
399 vulnerabilities on capability well-being, mental health and social support: an Austrian survey study. <https://doi.org/10.1186/s12889-021-10351-5>

400 [29] Sharma N Thakur K, Kumar N. [n.d.]. Effect of the Pandemic and Lockdown on Mental Health of Children. <https://pubmed.ncbi.nlm.nih.gov/32394157/>

401 [30] Emilia Vynnycky. 2010. *An introduction to infectious disease modelling*. Oxford University Press, Oxford.

402 [31] Umesh R Yadav. 2020. Home quarantine for primary, secondary contacts. <https://www.deccanherald.com/city/top-bengaluru-stories/home-quarantine-for-primary-secondary-contacts-853824.html>

403 [32] Xingxia Yu and Rongrong Yang. 2020. COVID-19 transmission through asymptomatic carriers is a challenge to containment. *Influenza and Other  
404 Respiratory Viruses* 14, 4 (2020), 474–475. <https://doi.org/10.1111/irv.12743> arXiv:<https://onlinelibrary.wiley.com/doi/pdf/10.1111/irv.12743>