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Response to the COVID-19: Understanding implications of government lockdown policies

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Abstract

The rising number of COVID-19 cases and economic implications of lockdown measures indicate the tricky balancing act policy makers face as they implement the subsequent phases of ‘unlock’. We develop a model to examine how lockdown and social distancing measures have influenced the behavioral conduct of people. The current situation highlights that policy makers need to focus on bringing awareness and social restraint among people rather than going for stringent lockdown measures. We believe this work will help the policy makers gain insights into the troubled COVID-19 times ahead, and based on the estimates, they can frame policies to navigate these wild waves in the best possible way.
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1. Introduction

The coronavirus pandemic, one of the biggest global threats has paralyzed the economies worldwide. The catastrophic impact of the pandemic gives it the power to change the policy frame of countries forever. The coronavirus pandemic is likely to weigh higher on a developing country (Walker et al. (2020)) because of the poor health infrastructure and surplus demand. While
the governments and the health personnel have been on their toes to curb the spread of COVID-19, the researchers have come up with several predictive epidemiological models to predict the estimated rise in the number of infected cases. These models aid policy makers to understand the severity of these diseases and plan the mitigation strategies accordingly.

The SIR model given by Kermack and McKendrick (1927) is one of the most popular epidemiological models used by scientists and researchers to study the spread of contagious diseases. Researchers have previously used the SIR model and its extensions to estimate the parameters of diseases. Deguen, Thomas, and Chau, (2000) used the SEIR model to estimate the contact rate of chickenpox in France. Bjørnstad, Finkenstädt, and Grenfell, (2002) studied the dynamics of measles epidemics using a time series SIR model. Demirci, Unal, and Ozalp, (2011) use a fractional SEIR epidemic model to analyze the disease-free state when the death rate is proportional to the population density. Najafimehr, Mohamed Ali, Safari, Yousefifard, and Hosseini, (2020); Liu, Gayle, Wilder-Smith, and Rocklöv, (2020); D’Arienzo and Coniglio (2020); Wang et al. (2020), and You et al. (2020) focus on estimating the basic reproduction number $R_0$. $R_0$ is defined as the average number of infections that an infected person can cause after getting into contact with the susceptible population (Bauch & Oraby, 2013).

Another area in the related stream analyzes the impact of different initiatives and policy measures to limit the spread of the disease. Bhar and Malliaris (2020) use econometric model to analyze the impact of unconventional monetary policy in easing the COVID-19 and relate it with the lessons learned from monetary policy during global financial crisis in US. Ferguson et al. (2020) consider the feasibility and impact of a set of suppression and mitigation measures on controlling the spread of COVID-19 in Great Britain and the US context. Alvarez, Argente, and Lippi, (2020) present an optimal lockdown policy in terms of the duration and strictness of lockdown measures with the objectives of minimizing the number of fatalities and lockdown costs. South Korea and Hong Kong have successfully limited the number of confirmed cases by leveraging civil society for pandemic management (Lee, Heo, and Seo, (2020); Wan, Ho, Wong, and Chiu, (2020)). Further, South Korea flattened the curve by combining testing, early isolation, and free treatment of positive cases with digital technologies without resorting to ‘lockdown’. It also disclosed all information on COVID-19 to the public in an open and transparent manner. In fact, South Korea’s response is considered as one of the most effective models against COVID-19 (UN-News, May 1 2020). China, too used citizen volunteers to work with the government to protect public health and to augment public services (Miao, Schwarz, & Schwarz, 2020). Several countries in Africa have either deployed or are considering using digital contact-tracing (DCT) to leverage unique institutional and technological characteristics and learnings from previous pandemics like Ebola (Arakpogun, Elsahn, Prime, Gerli, & Olan, 2020). Overall, numerous modeling efforts forecast the spread of the COVID-19 outbreak. While informative, these efforts have been generally limited to specific nations and snapshots in time.

Closer to our work, another stream of literature examines the impact of policy-related control measures on economic cost and the spread of COVID-19. Atkeson (2020) and Stock (2020) use the SIR model to predict the spread of COVID-19 in the United States by varying the level of mitigation measures from mild to severe. Acemoglu, Chernozhukov, Werning, and Whinston, (2020) extend the standard SIR model by including multiple demographic-based risk groups. They quantitatively investigate the optimal policy by analyzing the trade-off between efforts needed to save lives and improve economic indicators. Mahmoud et al. (2020) introduce a simulation tool, Flu And Coronavirus Simulator (FACS), that models the viral spread at the sub-national level, incorporating geospatial data sources to extract buildings and residential areas in a region. Using FACS, they model COVID-19 spread at the local level and provide estimates of the spread of
infections and hospital arrivals for different scenarios. Baker, Bloom, Davis, and Terry, (2020) assess the macroeconomic impact of COVID-19 by using three uncertainty measures. In the Indian context, Parbat and Chakraborty (2020) proposed a support vector regression model with Radial Basis Function as the kernel to predict the total number of deaths, recovered cases, the cumulative number of confirmed cases, and number of daily cases. However, their model predictions were made until June 2020. In another study, Chundakkadan and Ravindran (2020) found that internet inclusion is a relevant factor in the fight against the pandemic using the Google Search Volume Index for 33 Indian administrative zones (28 states and 5 union territories). They found that the information flow is inversely related to positive cases reported.

Through this work, we aim to contribute to the research methods and policy-related literature. We consider a set of policy measures taken by the Indian government to curb the spread of COVID-19. Since the first reported case in January, both state and central governments in India initiated various measures to tackle the spread of COVID-19. We analyze the impact of these measures in limiting the COVID-19 cases in India.

1.1. The Indian context

India, being the second most populous country globally, is struggling to flatten the COVID-19 curve. The COVID-19 pandemic has spread in all the States of India and has now become an alarming health threat. The exponential rise in the number of infections has pushed the resources to the brink; the hospitals are running short of health personnel, beds, and ventilators (Bal, de Graaff, van de Bovenkamp, and Wallenburg, (2020)).

Recently, a number of models and reports have been put forth by researchers and economists to predict the number of COVID-19 cases. However, a majority of these models make projections based on the specific epidemiological models only and miss out on the behavioral impact of individuals. The novel aspect of this study is to combine the SEIR epidemiological model with the system dynamics (SD) model. This combination allows us to incorporate the behavioral aspect of individuals in our model.

We formulate different scenarios to test the efficacy of specific government interventions such as a lockdown or a quarantine to control the COVID-19 spread. Our objective is to come up with a quantitative estimate of the impact that each policy is going to make. This estimate can help the policy makers to design an optimal policy response with an informed estimate of the impact the policy change is going to bring. Accordingly, they can decide about the number of medical facilities (number of beds, number of doctors, and number of personal protective equipment) that the government needs to create to facilitate the treatment of COVID-19 patients. Using the designed model, we can answer which intervention performs better than the other interventions and whether combined interventions might work better than the separate ones.

With the steepest GDP fall and the highest number of new COVID-19 daily cases globally1 the country has a lot at stake. The recovery critically depends on the set of policy measures taken by the Indian government. As the country relaxes one of the tightest COVID-19 lockdowns, the movement of workers to job locations will impact both the spread of the virus and the recovery of

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1 India has witnessed a GDP contraction of 23.9% in the first quarter of the year 2020, highest among the world’s top economies. The number of new COVID-19 cases are around 80000 each day. Retrieved from: https://www.nytimes.com/2020/08/31/world/asia/india-economy-gdp.html Accessed on: September 10, 2020.
country’s economy. The World Bank estimates a drop of 20% this year in the remittances from migrant workers of developing countries (India, Philippines, El Salvador, Mexico, Bangladesh) working overseas. This drop-off will affect millions of families, dependent on the cash for meeting their basic day-to-day needs. India’s huge population and its impact on the nations worldwide make this study relevant and insightful from the view of learnings on how to mitigate the pandemic crisis.

This paper is organized as follows. In Section 2, we discuss our research method and the corresponding tools used for conducting this study. We also present the models we have used to generate scenarios and study the impact of policy interventions in controlling the COVID-19. Section 3 presents the results. We conclude this paper in Section 4 with our findings. We present the limitations and future scope of work in Section 5.

2. Methods

We combine the SEIR epidemiological model with the SD tool for the purpose of this study. We divide the entire population into compartments as is the case in the SEIR model; however, we also take into consideration the behavioral factors and causal relationships which impact the spread of COVID-19 disease. We develop the causal relationships with the use of SD tools. We make use of the causal loop diagram (CLD) to understand the factors which play a major role in the spread and containment of COVID-19. We have incorporated these relationships in the SEIR model to facilitate a comprehensive analysis. Next, we explain the basics of SEIR and SD modeling. We have used SEIR and SD as the base models in developing the designed model.

2.1. Introduction to the base models used in the study

2.1.1. SEIR epidemic model

SEIR is a compartment based model used to study the spread of an infectious disease. The model divides the population into four compartments (i) Susceptible, (ii) Exposed, (iii) Infectious, and (iv) Removed. This model derives from the classical SIR model (Kermack & McKendrick, 1927). In the SIR model, the population is segmented into three compartments (i) Susceptible, (ii) Infectious, and (iii) Recovered. The last compartment is often called as removed. The population starts from the susceptible compartment and progresses through the latter two compartments on getting infected and finally on recovery. This is the most basic mathematical epidemiological model. However, this three stages SIR model is not able to describe the spread of all infectious diseases. For some diseases, such as smallpox, tuberculosis, and COVID-19 there is a delay between the time a person gets infected and the time when the person becomes infectious. Thus, it becomes necessary to consider a latent compartment for the infected (but not infectious) individuals. The presence of the latent period for such contagious diseases makes the SEIR model more appropriate to analyze the associated spread. Therefore, we use the SEIR model, which is an extension of the SIR model with an added compartment of Exposed (but not infectious). The mathematical details of the SEIR model are provided in the Appendix A.

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2 Retrieved from: https://www.wsj.com/articles/indias-migrant-laborers-begin-heading-home-as-coronavirus-lockdown-eases-11589196559 Accessed on: September 10, 2020.
3 Retrieved from: https://www.wsj.com/articles/developing-world-migrant-workers-remittances-coronavirus-pandemic-lockdown-reopen-11593969595 Accessed on: September 10, 2020.
2.1.2. System dynamics model

SD (Forrester (1961); Sterman (2000)) as a modeling tool is used to predict the potential futures of a complex system and analyze the impact of changes in the system behavior. The benefit of using SD is that it can handle non-linear characteristics (Sterman, 2000). Using the CLD (an SD tool), we can plot the causal maps to explore how the different parts of a system affect each other. Thus, we can get an idea of the critical components and relationships which significantly control the behavior of the system. The causality can be one or both ways. There are balancing loops which diminish a change over time and reinforcing loops, which amplify a change leading to a large impact on the system over a period. SD is especially suited for studying a pandemic. The tool provides a systematic and concise way to study the interactions of social, demographic, and policy-related processes that govern the spread of a pandemic. We use SD to model the spread of COVID-19 when government policies are in place to control the spread. With the stock and flow diagram (SFD), we analyze the changes in the number of individuals belonging to different compartments of the SEIR model upon the implementation of policy measures. We carry out the simulation starting from the date January 30, 2020 for a period of 1000 days.

2.2. Designed model

For studying the dynamics of COVID-19, we combine the SEIR model and the SD tool. To capture the real-life scenarios, we have relaxed a major assumption of the basic SIR model, which states that the total population remains constant while the epidemic lasts. To account for this relaxation, we incorporate the birth rate and death rate in our model. This makes our model more reliable and closer to the reality. Further, we have added relevant behavioral factors into the base SEIR model by using SD tool. This helps us to identify the various feedback loops and cause-effect relationships, which are vital in predicting the impact of different precautionary measures.

2.2.1. A causal map for the spread of COVID-19

In this section, we present a CLD to explain the relationship among various factors (related to government policies, people’s behavior), which affect the number of COVID-19 infected individuals. The model considers the impact of different policies on behavioral change among individuals and effective contact density. The number of infected individuals depends on the interrelationship between multiple causal loops. We present the detailed diagram in Fig. 1.

We explain the balancing and reinforcing loops of the CLD below. B1 and B2 loops are balancing loops. A balancing loop lowers the change in the direction of the loop (Kim (1995)). R1 is a reinforcing loop. In a reinforcing loop, changes compound over time in the direction of the loop (Kim (1995)).

**B1 Loop: Susceptible population adjustment loop** (left part of the figure): more the number of susceptible people, more will be the number of people exposed to the disease. Exposed population eventually becomes symptomatic over the incubation period and results in an increase in the infected population. The increase in the infected population increases the number of deaths forcing the government to put in more stringent measures like enforcement of lockdown and travel restrictions. These restrictions lead people resorting to self-isolation, and as a result, the susceptible population decreases.

**B2 Loop: Transmission rate adjustment loop** (right part of the figure): the population exposed to disease advances to become symptomatic and infectious. More number of infected people lead to more deaths, which stimulates behavioral changes in people (frequent handwash, meeting less
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Fig. 1. Causal loop diagram explaining the cause-effect relationships for COVID-19.

number of people daily, and social distancing). The behavioral changes reduce the environmental contamination and hence lead to a decline in the rate of transmission of the disease.

**R1 Loop: Infected population growth loop** (center of the figure); more the number of infected people, more will be the contact with the susceptible population, which, in turn, will increase the number of people exposed to the disease. These exposed people will eventually become symptomatic over the incubation period.
2.2.2. Stock and flow diagram

While the CLD emphasizes the feedback structure of the system, it cannot comprehensively present all the details of the system. Converting a CLD into an SFD is necessary to pinpoint the physical structure of the model. SFD can be used for simulation, sensitivity analysis, scenario building, and policy analysis. We present the SFD for the proposed model in Fig. 2.

We can observe in Fig. 2, there are seven stocks. The base SEIR model has four different types of stock. We have added two stocks (total population and self-isolated population) to see the impact of various policy interventions and behavioral changes when the total population is not constant. A set of equations and variables govern the stocks and flows. We explain these in Appendix B. Other than the equations, we have used a few parameters in the model. We discuss the data sources for parameters’ values in Appendix C.
2.3. Scenario building

We present the control measures taken by the Indian government in response to the COVID-19 in Fig. 3. Based on the government’s control measures we consider five scenarios, namely, 1. no intervention, 2. light intervention, 3. moderate intervention, 4. strict intervention, and 5. actual intervention. We summarize the parameter values for these scenarios in Table 1.

We explain these scenarios below.

1 **No intervention (Scenario 1):** In the first scenario, there is no intervention by the policy makers to either suppress or mitigate the impact of COVID-19. No lockdown or restriction on mass gathering is imposed. In this scenario, we expect to observe a small degree of change in people’s behavior (i.e., proportion of people self-isolating, decrease in the contact with other people) when the number of cases becomes significantly large. To model this scenario, we set the impact of behavior change and the % decrease in contacts at 25% with a delay of 50 days in behavior change. We also assume that 40% of the population goes into self-isolation after the initial 30 days.

2 **Light intervention (Scenario 2):** In this scenario, we predict the dynamics of COVID-19 in the presence of light intervention by the policy makers. We model light intervention as a scenario where the government does not impose a complete lockdown and movement restrictions but only limits itself to issuing warnings against the spread of COVID-19, promoting awareness programs to bring about behavioral change in people. Under such a scenario, we expect to observe a higher degree of change in people’s behavior than when policy makers do not make any intervention. To model this scenario, we set the impact of behavior change and the % decrease in contacts at 35% with a delay of 40 days in behavior change. We also assume that 50% of the population goes to self-isolation after the initial 25 days.

3 **Moderate intervention (Scenario 3):** Under the moderate interventions scenario, we model the restrictions put up by policy makers to be more stringent (partial lockdown, movement restriction). We expect to observe a better response from the population in terms of behavior change to tackle the spread of COVID-19. To model this scenario, we set the impact of behavior change and the % decrease in contacts at 40% with a delay of 30 days in behavior change.
Table 1
Parameter values for different scenarios.

| Parameters                        | Scenario 1 No intervention | Scenario 2 Light intervention | Scenario 3 Moderate intervention | Scenario 4 Strict intervention | Scenario 5 Actual intervention |
|----------------------------------|----------------------------|--------------------------------|----------------------------------|-------------------------------|--------------------------------|
| Ro                               | 2.5                        | 2.5                            | 2.5                              | 2.5                           | 2.5                            |
| Number of cases imported         | 3                          | 3                              | 3                                | 3                             | 3                              |
| Time taken by foreign cases to come in % decrease in contacts | 0                          | 0                              | 0                                | 0                             | 0                              |
| Impact of behaviour change       | 25%                        | 35%                            | 40%                              | 50%                           | 25% (first 55 days), 70% (in lockdown), 60%, 50%, 40% (in unlock 1,2,3 respectively) |
| Delay in behaviour change        | 50 days                    | 40 days                        | 35 days                          | 30 days                       | 30 days                        |
| Fraction of people self-isolating | 40%                        | 50%                            | 55%                              | 60%                           | 60%                            |
| Self-isolation start time        | 30 days                    | 25 days                        | 25 days                          | 20 days                       | 55 days                        |
| Incubation time                  | 14 days                    | 14 days                        | 14 days                          | 14 days                       | 14 days                        |
| Fatality rate                    | 1.5%                       | 1.5%                           | 1.5%                             | 1.5%                          | 1.5%                           |
change and the % decrease in contacts at 40% with a delay of 35 days in behavior change. We also assume that 55% of the population goes to self-isolation after the initial 25 days.

4 **Strict intervention (Scenario 4):** In this scenario, we model the strict interventions of the policy makers to control COVID-19. We have considered strict interventions to be the case in which a complete lockdown is imposed for an extended duration, local businesses are shut down, and the movement of people is highly restricted. We expect to observe the highest degree of change in people’s behavior under this scenario. To model this scenario, we set the impact of behavior change and the % decrease in contacts at 50% with a delay of 30 days in behavior change. We also assume that 60% of the population goes to self-isolation after the initial 20 days.

5 **Actual intervention (Scenario 5):** In this scenario, we try to model the actual actions taken by the policy makers and accordingly adjust the parameter values with time. We have observed that in India, the government started with light warnings to adopt precautionary measures against COVID-19 (late February to early March), which later on changed to a very strict lockdown, closing down of businesses, restriction on movement of people, suspension of all international flights (late March till mid-May) and then slowly the government allowed the businesses to open up and also eased the movement of people. To model this scenario, we set the self-isolation start time to 55 days, with 60% of the population going into isolation. The impact on behavior change and the % decrease in contacts change from 25% (for first 55 days) to 70% (for the lockdown phase), and during the subsequent unlock phases, they become 60%, 50%, and 40%, respectively. The gradual decrease percentage is based on Google mobility report mentioned in Appendix C.

2.4. **Model validation**

Modeling is an iterative process of communicating, testing, modifying, and validating the developed model at every stage. Model validation is an important process of establishing confidence in the robustness and usefulness of a model. Although validation takes place throughout the process, the formal validation framework roughly consists of two phases that needs to be followed subsequently. The first step is to check whether the model complies with the common sense of the actors within the system. This phase is called structural validation. The next step is to measure how accurately the model can reproduce major behavior patterns of the real system; this phase is called behavioral validation. We have conducted behavioral reproduction tests, extreme conditions test, anomalous behavior test, and dimensional consistency test to establish the validity of our model. We list down the details and results of these tests in the Appendix D.

3. **Results**

The results of all the scenario are shown graphically in Fig. 4. The model predicts that without any policy intervention in place, the maximum number of active cases will peak after 220 days at 180 million cases. The total number of deaths is predicted to be around 12 million, while the recoveries are around 750 million. These numbers indicate the severity of COVID-19 and call for greater policy interventions by the government.

In the subsequent scenarios with light and moderate interventions, respectively, the spread of the disease is slightly delayed with a peak number of active cases observed after 300 days and 380 days, respectively. The maximum number of active cases, deaths, and recoveries are also reduced. However, the number of active cases will still exceed the resource capacity of India. With a strict policy intervention, the model predicts the maximum number of active cases to peak
after 600 days to approximately 45 million cases. The total number of deaths is predicted to be around 6 million, while the recoveries are around 400 million. These numbers suggest that a strict policy intervention will delay the peak of the disease substantially. However, having a strict policy intervention like ‘complete lockdown’ for such a long duration is not sustainable for the economy.

Finally, we analyze the impact of actual interventions by the Indian government. The model predicts the number of active cases to spike sharply once the ‘lockdown’ phases get over, and the country goes into the subsequent phases of ‘unlock’. The model predicts the active number of cases to peak after 300 days to approximately 50 million cases. The total number of deaths is predicted to be around 7 million, while the recoveries are around 450 million. These numbers suggest that the policy intervention by the Indian government have helped in delaying the spread of COVID-19. However, with the ease of strictness, the number of infections is expected to go up, and this will again put pressure on the health care resources of the country.

4. Conclusions

The parameters’ values we have used in our model have been taken as per India’s reported data. This model can be configured for other countries by substituting country-specific socio-economic conditions, macroeconomic indicators, policy regime, and citizen awareness and motivation for leveraging voluntary civic participation to protect public health and augment public services.

The novelty of this work lies in the incorporation of SD with the SEIR model to analyze the policies’ impact in controlling the spread of COVID-19. This unique approach has not been discussed in the literature so far. This combination helps to incorporate the behavioral aspect of individuals in the designed model. In the case of COVID-19, the success of a policy depends
on how well the citizens follow the social distancing and hygiene norms. Therefore, with the inclusion of the behavioral aspect, we can get reliable causal relationships and robust results.

The causal diagram can be used by policy makers to identify the crucial factors that significantly impact the rise in the number of COVID-19 cases. To design an optimal policy response, the focus needs to be on controlling these crucial variables. The policy makers can estimate the requirement of health resources based on the predicted COVID-19 cases. The model output shows that policy interventions by the Indian government have helped in slowing down the spread of COVID-19 in the initial phases; however, our model shows that similar results could also have been achieved with moderate level of interventions.

The spread of COVID-19 in India is observed by the entire world due to its large population and its implications on the other nations. While the actions by the Indian government in the initial phase have been commendable and rightly appreciated by other countries, the country still needs to put in more efforts to keep the disease in check. A strict lockdown as the solution approach is not viable because of the severe economic impact (Forman, Atun, McKee, and Mossialos, 2020). Salvatore (2020) highlights that the emerging economies have already become financially vulnerable because of falling primary exports owing to the reduced global demand. With the economies worldwide heading for a global recession in the ongoing pandemic era (Nasir, 2020; Shiller, 2020), any further implementation of lockdown is going to be devastating for the country’s economic growth. Therefore, the policy makers need to create awareness among individuals to make changes in their habits and include precautionary measures in their lifestyle such as frequent washing of hands, use of masks and sanitizers, and maintenance of social distance while going out. All these behavioral changes will reduce the transmission of COVID-19 and thus will bring a definitive impact in checking the pandemic’s spread.

5. Limitations and future scope

The proposed model makes predictions about the dynamics of COVID-19 spread with the assumption that no vaccine will be available in the near future. The severity of the spread can be significantly controlled if a vaccine becomes available. The model is at the country level and the geographical aspects of the local region, the dynamical movements, and the interaction of people within it have not been considered. We have also not considered other governmental and non-governmental interventions and their implications such as food insecurity, nutritional status, productivity, education, and wage earnings, the economic slowdown, unemployment rate, the survival of micro, small, and medium enterprises, and impact of migrant workers. The use of mobile caller tune and digital platforms to spread awareness about COVID-19 as one of the containment measures of government too could not be incorporated in our model. Further, in this modeling exercise, we have not accounted for the limitation in the resources such as the number of hospital beds, doctors, testing capabilities, and financial resources available to the government (owing to lack of data availability). Effects of civic participation and voluntary engagement of citizens and businesses community could have been considered as in the case of South Korea (Lee et al., 2020), Hong Kong (Wan et al., 2020), and China (Miao et al., 2020). The inclusion of all these inputs in modeling can lead to more reliable predictions. Going forward, researchers may include these inputs in their models to come up with more robust results.
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Appendix A. SEIR epidemic model

The SEIR model is described by a system of non-linear ordinary differential equations. Let $S(t)$, $E(t)$, $I(t)$, and $R(t)$ denote the number of susceptible, exposed, infected and removed individuals at time $t$, respectively. The set of rate equations that characterize the transition across the four segments of the SEIR model are given below.

\[
\frac{dS}{dt} = \Lambda - \mu S - \frac{\beta S(t)I(t)}{N} \tag{1}
\]

\[
\frac{dE}{dt} = \frac{\beta S(t)I(t)}{N} - (\mu + a)E(t) \tag{2}
\]

\[
\frac{dI}{dt} = aE(t) - (\gamma + \mu)I(t) \tag{3}
\]

\[
\frac{dR}{dt} = \gamma I(t) - \mu R(t) \tag{4}
\]

where, $\Lambda$ denotes birth rate, $\mu$ denotes death rate, $\beta$ is the average number of contact per person per time multiplied by the probability of disease transmission in a contact between a susceptible and an infectious subject, $a$ denotes the incubation period, and $\gamma$ is the inverse of duration of the time an individual remain infectious.

Appendix B. Equations used in the SFD

Following equations govern the stocks and flows in the system dynamics model used in the manuscript.

Total Population = Initial Population + \int_{0}^{t} (Birth − Death) dt \tag{5}

Susceptible Population = Initial Population + \int_{0}^{t} (Birth − Death − Infections − Self Isolation) dt \tag{6}

Population Exposed to Disease = \int_{0}^{t} (Infections − Advancing to Symptomatic) dt \tag{7}

Infected Population = \int_{0}^{t} (Advancing to Symptomatic + Cases from Foreign Land − Recovery Rate − Death Rate) dt \tag{8}
Numer of People Died = \int_0^t (\text{Death Rate}) \, dt 

Recovered Population = \int_0^t (\text{Recovery Rate}) \, dt 

Infections = \text{Infected Population} \times \text{Rate of Transmission} 

The SEIR model differs from the SIR model because of the presence of the exposed compartment. The exposed population is not infectious initially but it becomes symptomatic and infectious over the incubation period. This has been captured by following equations:

\[
\text{Advancing to Symptomatic} = \frac{\text{Population Exposed to disease}}{\text{Incubation Time}} 
\]

\[
\text{Fraction Susceptible} = \frac{\text{Susceptible Population}}{\text{Total Population}} 
\]

The awareness programs and other interventions by the policy makers will bring change in the regular habits of individuals. They are then likely to come in contact with less number of individuals on a daily basis. This will lead to a reduced contact density and effectively help in curbing the spread of the disease. This part has been captured through the following equations:

\[
\text{Effective Contact Density} = \frac{\text{Normal Contacts}}{1 + \% \text{Decrease in Contacts} \times (1 - \text{Fraction Susceptible})} 
\]

\[
\text{Transmission Rate (original)} = \frac{R_0}{\text{Duration of Disease}} 
\]

\[
\text{Rate of Transmission} = \text{Effective Contact Density} \times \text{Effective Behavioral Change} \times \text{Fraction Susceptible} \times \text{Rate of Transmission (original)} 
\]

We have assumed that the behavioral changes in the people will be induced over a period of time rather than being instantaneous. To capture this, we have included a variable named ‘delay in behavior change’.

\[
\text{Effective Behavioral Change} = \text{SMOOTH3}(1 - \text{STEP (Behavior Change Impact, Time taken by Foreign Cases to come in), Delay in Behavior Change}) 
\]

To keep the model simple and tractable, we have assumed that all the cases which come from foreign lands to India, come at same time rather than being spread over time. Similarly, we have assumed the people to go to self-isolation at same time rather than building up slowly up to a certain fraction:
Appendix C. Data sources

We use a number of variables and parameters in our model. Here, we provide their brief description and list down the sources from where we draw these parameters’ and variables’ values.

- **Initial population:** We run the simulation for 1000 days starting January 30, 2020. The initial population refers to the population of the country at the onset of the disease. We have taken the initial population to be 1.38 billion. The population data is available at https://www.worldometers.info/world-population/india-population/.
- **Birth/day and Death/day:** These are the number of births and deaths which occur naturally and not due to COVID-19. The values of birth/day and death/day are taken to be 73,787 and 26789, respectively. The corresponding data is available at https://www.medindia.net/patients/calculators/pop_clock.asp.
- **Normal contacts:** A number of studies have been carried out which estimate the number a contact a person has in a single day. Leung, Jit, Lau, and Wu, (2017) estimate the number of contacts per day in different countries for different age groups and report values ranging from 1.5 to 5.5. For the purpose of this study, we take a value of 5 for the normal contacts per day in India.
- **R0:** It refers to the number of persons to whom an infected person can spread the disease. We adopt a value of 2.5 from the study conducted by Zhang et al. (2020).
- **Duration of disease and Incubation time:** Incubation time is the period in which an infected person becomes symptomatic and infectious. While the duration of the disease is the number of days a person takes to recover from the disease. We have taken a median value of 14 days for both of these parameters; the corresponding reports and data are available at https://www.cdc.gov/coronavirus/2019-ncov/hcp/clinical-guidance-management-patients.html.
- **Fatality rate:** It is the ratio of the number of deaths to the number of cases reported for COVID-19. In India, the fatality rate is currently under 2% and is declining with time. We take a value of 1.5% for the purpose of this study. The corresponding data has been reported at https://www.bloombergquint.com/coronavirus-outbreak/india-covid-19-fatality-rate-falls-to-193-recovery-rate-nears-72.
- **Number of cases from foreign land (immigrants):** These are the number of infected people who entered India to trigger the onset of the disease. We have taken this value to be three as per the number of cases data reported by https://www.covid19india.org/ on January 30, 2020.
• **Time taken by foreign cases (immigrants) to come to India:** We have run the simulation starting from January 30, 2020 when the 3 cases from foreign land had entered India. Hence, we take a value 0 for this parameter.

• **% decrease in contacts, impact of behavior change, and fraction of population self-isolating:** These values have been estimated by using Google’s community mobility reports for India. The Google’s community mobility reports for India is available at https://www.gstatic.com/covid19/mobility/2020-08-21_IN_Mobility_Report_en-GB.pdf. Further, estimation of the percentage decrease in the number of visits to parks, pharmacies, retail stores, transit stations, workplaces, and residential places has been done using these reports. It is available at https://towardsdatascience.com/how-did-lockdown-impact-our-daily-movement-f9da2ed264d7.

### Appendix D. Model validation

#### Extreme conditions test

Models must be robust and behave appropriately under all potential circumstances, even including extreme conditions that have never been observed in the real world. Extreme condition tests are usually used for testing the robustness of the model structure. They test whether models behave appropriately when the inputs are assumed to take on extreme values. Extreme conditions are set with the number of immigrant cases, taking extreme values of ‘0’, which is impossible in reality. The assumption is that if no infected person enters the country, there would be no case of COVID-19 in India. The model indeed shows zero cases over the duration of simulation when the number of immigrant cases is set to ‘0’.

#### Behavioral reproduction test

Dynamic simulation models offer a consistent basis for predictions. This basis is a consolidation of judgment, experience, and intuition that has been tested against historical evidence, and the predicted effects of implementing alternative policies are promptly available. Confidence in the model is reinforced if the model replicates long-term historical behavior.

We test our model to check that the output of the model approximately matches the historical data points (Fig. 5). The base run was for the initial 200 days (for which the actual data is available). We plot the model output against the actual values in Fig. 5. We find the average deviation in the number of active cases, the number of deaths, and the number of recoveries to be 11183, 1252, and 11550, respectively. All the deviations are less than 2.5% of the corresponding total numbers till the 200th day.

#### Anomalous behavior test

The developed model replicates the behavior of the real system for the entire range of parameter values. No discrepancies were found during the behavior anomaly test.

#### Dimensional consistency check

We test for dimensional consistency using units check in VENSIM. All the units were found to be consistent.
Fig. 5. Model predicted result vs Actual result. The average deviations are less than 2.5%.
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