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Research Article

A General Linear Model Approach to Determine the Effect of Un-lockdown on COVID-19 Pandemic in New Delhi

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A B S T R A C T

Introduction: As new strains of SARCOV2 virus emerge across the world, it is imperative to investigate measures which restrict the movement of the general population such as social and travel restrictions by lockdowns to mitigate the effects of COVID-19. Thus, our paper helps in two ways: 1) Drastic measures like lockdown are essential but cannot be a feasible long-term intervention. Therefore, it is crucial to understand if the same unlock down can be reversed without compromising public health needs. Our paper provides evidence on the same; and 2) Our report also provides an insight into the trends of disease transmission during different phases of the un-lockdown.

Methods: We examine the spread of pandemic during different phases of Un-lockdown (8th June to 31st October 2020). Since R_t calculation takes into consideration numerous factors, we use β, the transmission coefficient that governs the transition of population from Susceptible to Exposed pool, to examine the effect of public heaThelth interventions on disease spread.

Results: The comparison of the distribution of fitted β values, thus calculated using SEIR model and GLM have been done and a Welch Two Sample t-test suggests that the GLM fitted β and SEIR β data sets are not significantly different from one another.

Conclusion: We provide evidence that un-lockdown can be achieved without increasing the transmission of disease disproportionately. Thus, a phased wise approach to un-lockdown is encouraged. We also provide the rationale for using β over R_t values to specifically assess the effect of public health interventions designed to decrease exposure.

Keywords: COVID-19, Pandemic, Transmission Coefficient, Lockdown

Background

Starting with a case of atypical pneumonia in Hubei province of China in December 2019, the infection we now know as COVID-19, continues to pose a challenge to all the countries, their governments and their people worldwide.[1] The virus itself has infected over 262,995,297 people and claimed nearly 5,219,398 lives in over 212 countries as of 1st December 2021.[2] The mitigation strategies (such as lockdown) to control the pandemic themselves were also proving to be a double-edged sword - putting strain on the economy, disrupting supply chains of essential commodities including healthcare and creating a problem of access and utilisation of healthcare services to name a few. It is thus imperative to weigh carefully the benefits and risks associated with these strategies, so policymakers can make timely and informed choices to tackle the pandemic while minimising the collateral damage it causes to other public services. In this article, we examine one such mitigation strategy, the lockdown and un-lockdown, in the context of the national capital territory (NCT) of Delhi - the capital of India.

India and Delhi's Response to COVID-19

As of 1st December 2021, a cumulative total of COVID-19 cases in India and Delhi were 34,596,776 and 1,440,934 respectively, and the death tally stood at 469,247 and 25,098 respectively.[3] The government of India, along with the respective state governments has adopted an multi-pronged approach to contain the pandemic over the year.[4] The facets of this approach were - travel restrictions (including an early ban on international travel), advisories on personal safety measures like social distancing, hand hygiene and mask-wearing, active tracing of cases, institutional isolation based on the severity of infection, extensive and countrywide lockdown.

For a country of more than a billion people and with very resource-constrained healthcare infrastructure, the multi-phased lockdown of more than 3 months allowed the government to do the much needed "upscaling" of healthcare infrastructure. To keep the benefits of lockdown intact, the government decided to divide different areas in red, orange and green zones, based on the number of active cases. Un-lockdown was implemented in a phased manner– lifting restrictions from green zones initially, allowing essential activities to resume first and allowing only limited travel within and outside the country in the first few days. While the country was going through these phases of un-lockdown, two important things were happening simultaneously. On one hand, the government was upscaling of healthcare infrastructure (including expansion of isolation facilities, treatment options and testing capacity) which was meant to keep the pandemic under control, while simultaneously more people were getting exposed to the infection as restrictions were being relaxed, which could potentially flare up the pandemic.

The government of NCT of Delhi was also faced with a similar situation when trying to balance the benefits of the various mitigation strategies and their impact, especially in areas with high population density, poor housing, migrant population, and those with limited to poor water and sanitation facilities. It is thus, vital to analyse this conundrum in Delhi's context to see the effect of un-lockdown on the control of pandemic. We have attempted to assess the effect of un-lockdown by examining the epidemiological and temporal spread of the COVID-19 pandemic during the time - period 8th June to 31st October 2020, as we passed through the various phases of un-lockdown in the NCT of Delhi.

The following are the objectives of this research paper: 1) To assess the spread of the pandemic during phased un-lockdown in the NCT of Delhi; 2) To use a mathematical model to determine the effect of un-lockdown on the transmission of COVID-19 infection; and 3) To empirically compare the results obtained from analysing R_t values and those obtained from β values.

Methodology

The study was done by using Infectious disease modelling methods by using two variables, period of lock down in Delhi NCT, and Day wise new cases, recoveries and deaths in the NCT of Delhi available for COVID19 from public domain.

We wanted to examine the spread of pandemic during different phases of Un-lockdown, that is, during the time period 8th June to 31st October 2020. The reason for taking the cut off for un-lockdown and data analysis as 31st October 2020 are as follows:

- The un-lockdown was meant to resume daily activities and function to a near-normal (that is pre-COVID) state. As is stated in Table 1, most of the activities had resumed back to the near-normal/ pre-COVID state by this time
- After October 2020, Delhi saw a rise in the number of COVID-19 cases once again, leading to the second wave. The mitigation strategies for the second wave were different from the first wave in a lot of ways, the most important being a lack of complete state-wide lockdown. Thus, to get an accurate assessment of the spread of the infection during the un-lockdown period, data beyond this point (31st October, 2020) was not taken

For our independent variable - the un-lockdown, we split the time duration into various phases depending on resumption of activities and lifting off major restrictions that allowed citizens to move out of their homes and thus potentially increased the risk of exposure of the susceptible

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population to the infected people and thereby increasing the probability of acquiring infection. The division along with the description of activities resumed is given below

Table 1.Phases and Activities of Un-lockdown as implemented in India

Phase	Dates	Major Activities Resumed
Phase I	8th to 30th June 2020	From June 8th shopping malls, religious places, hotels and restaurants reopened. Night curfew was applicable from 9 pm to 5 am. 200 special trains were resumed.
Phase II	1st to 31st July 2020	Only Containment zones were under lockdown. Most activities were permitted in all other areas. Intra- and inter-state travel was permitted.
Phase III	1st to 31st August 2020	Night curfews were removed. Gym and yoga centres were reopened.
	1st to 30th September 2020	Metro rails reopened from September 7. Gatherings allowed - marriage (50 people allowed), funereal/ last rites ceremonies (20 people allowed), religious, entertainment, political, sports, academic functions and gatherings (100 people allowed). Face coverings/ masks were made compulsory in public places, workplaces and during transport.
Phase V	1st to 31st October 2020	Swimming pools being used for training of sportsperson opened. Cinema halls opened with 50% seating capacity.

(Table 1).[5]

Day wise data of new cases, recoveries and deaths in the NCT of Delhi were retrieved from covid19india.org.[3]

Finally, to empirically compare the results obtained by using β values and those obtained by using R_t values we analysed the temporal trends between the two results. This was done by comparing the time of fall and rise in R_t values with that in β value.

Mathematical Model

To achieve the desired objectives, we have used two mathematical models to assess the effect of the public health interventions policies on the transmission of the disease. Firstly, using an SEIR (Susceptible, Exposed, Infected and Removed) model, the transmission coefficient β (Figure 1) was calculated for each of the above-mentioned phases of un-lockdown. As described by Yap FF et al.,[6] β is the "transmission rate per infectious individual", which gives the number of new infections generated per day. Surveillance data were fed into the EpiNow calculator,[6] which used the SEIR model for transmission coefficient β. After obtaining valid results from this model, a Generalised Linear Model (GLM) was formulated using three variables - active number of cases at the corresponding date, the strictness of lockdown (measured in percentage, where 99% refers to near-complete lockdown) and the past 7-day average value of β. This model allowed us to mathematically calculate and analyse the effect of various phases on un-lockdown on the spread of the disease. Finally, we compared the distribution of the GLM fitted β*t* and SEIR fitted β*t*.

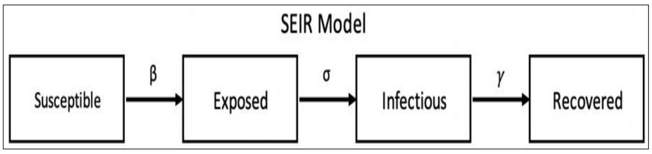

Figure 1.SEIR Model

SEIR Model in Context of New Delhi

The mean latency period is assumed to be 5 days.[7] The rate of persons moving from the exposed to the infected state is denoted by a latency coefficient (σ), which can also be understood as the inverse of the latency period, hence, σ = 0.2. Similarly, the mean infectious period is assumed to be 2 days.[6] The rate of persons moving from the infected to the removed state is denoted by the coefficient γ, which can be understood as the inverse of the infection period, hence, γ = 0.5.

Here, β denotes the transmission coefficient. Additionally, β is made to vary based on the week in question; for instance, β_1 is the coefficient assigned to the dates from 1st to 8th March 2020.

Further, initial conditions are set for each state S, E, I and R:

S = 20 million; E = 0; I = 0.71163; and R = 1.

Using this, these differential equations can easily be solved using Euler's method (by utilising the deSolve functionality in R).

SEIR Model Assumptions

S(t), E(t), I(t) & R(t) denotes the number of persons in the susceptible, infective, exposed and removed class respectively, at any given time t.

The following assumptions have been made:

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Each class is considered to be a continuous variable due to the large (and assumed constant) population size N. Births and natural deaths have not been accounted for, as India's population growth rate (0.99% annually) would have had negligible effects (for the given time period) on the already massive population. The entire population is susceptible to the infection.

The population experiences homogenous interaction. "Interaction" refers to contact between persons in the population. "Infection" refers to the interaction between a susceptible and infective that results in the transmission of the disease. The rate of transmission from Susceptible to Exposed is denoted as β.

Individuals are removed from the infective class at a rate γ, called the daily removal rate. The recovery rate is also assumed to not vary seasonally.

SEIR Model Formulation

Let X_t be a random variable denoting the number of reported cases at any time t. Assuming X_t follows a Poisson distribution with parameter λ_t (the fitted number of confirmed cases).

$$P(X_t = x_t) = \frac{(\lambda_t)^{x_t} e^{-\lambda_t}}{x_t!}$$

Parameter value for $I_{(t=0)}$ and all β_i are set, such that the log-likelihood function is maximised. Now, the smallest observed value of x_i is 1, while the maximum is 3,86,706. For such large values, quantification of Poisson probabilities is extraneous; hence a normality assumption is made here. The random variable is now assumed to (approximately) have a Gaussian distribution. Hence,

$$X_t \sim N(\lambda_t, \lambda_t)$$

Using an OLS methodology allows for the estimation of the parameters ($I_{(t=0)}$ and all β_i) by minimising the Chi-squared error parallel also conforming to the normality assumption. For this, the following function needs to be minimised,

$$\sum_{\forall t} \frac{(x_t - \lambda_t)^2}{\lambda_t}$$

The minimised value of the aforementioned (Chi-squared) statistic was computed to be 446.991. The graph below represents the fitted value of β_i for the i^{th} week starting from 01st March 2020 (Figure 2).

The error (actual - fitted) from the SEIR model, where the 'actual' refers to the cumulative reported cases, and the 'fitted' refers to the number of persons in the Removed (R) state at any time t, is assumed to be normally distributed. Consequently, for the SEIR model, the error term, e_t varies normally with a mean of 3.75, and standard deviation of 292.98, i.e.,

$$e_t \sim N(3.75, 292.98^2)$$

A one-sample t-test on this error term provides a 95% confidence interval of (-33.19,40.69), with a p-value of 0.8416. Which is indicative of insufficient evidence being available to reject the H_0 (i.e., the true mean being equal to zero). Hence the true mean is not significantly different from the empirical mean of e_t. Thus, this error term can be considered to be a zero-mean white-noise process with a

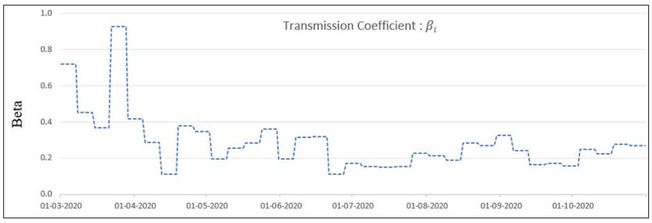

Figure 2.SEIR Fitted Values of βi over the Period of March'20 to October'20

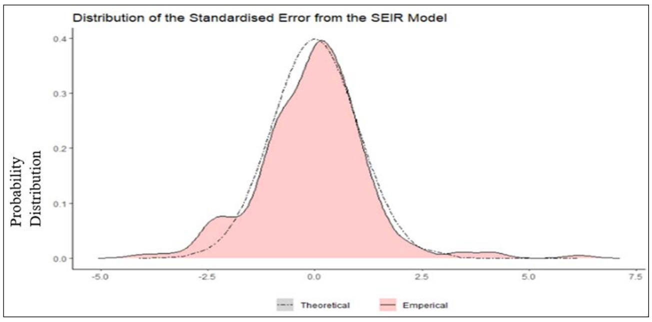

Figure 3.Distribution of the Standardised Error from the SEIR Model

homoscedastic variance, denoted by σ^2. Here, $\sigma^2 = 292.98^2$.

The error (actual-fitted) from the SEIR model was tested for zero-mean white noise process (Figure 3). One sample t–test was applied to check whether the true mean is significantly different from the empirical mean of error term. Since this is a temporal model accounting for day-wise changes and

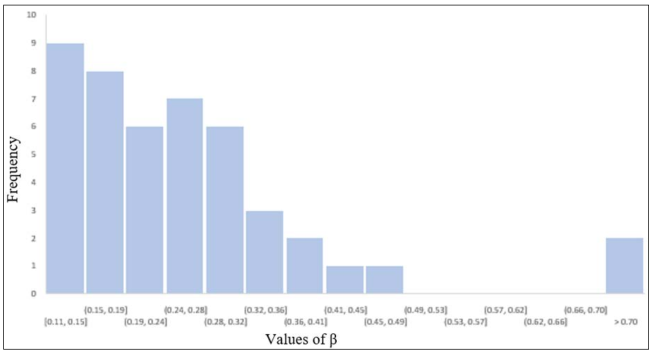

Figure 4.Distribution of Beta

autoregression is likely to be present. Thus, instead of a simple linear regression, GLM was applied.

GLM Formulation

In order to treat β_i as a random variable (and model it), its distribution must be known. β_i is assumed to be a continuous function of time, of which only the (discrete)

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weekly values are known. Thirty-six such discrete values of β_i are ascertained using the SEIR Model. These figures are considered to be constant over the respective week.

The above graph (Figure 4) allows for the assumption that β is positively skewed. Also, $\beta \epsilon [0,\infty)$. Thus, β can be assumed to follow a Gamma distribution. Numerous factors affect the transmission of a virus.

Table 2.Covariates in Gamma based Generalised Linear Model

A_i	Active number of cases at the corresponding date
$R_i \epsilon [0,1]$	Strictness of lockdowns (0% implying no restrictions etc)
(β^7)	Corresponds to the past 7-day average value of β

Here, in the formulation of a Gamma based Generalised Linear Model, the following covariates are being considered (Table 2).

As discussed, the latency period is assumed to be 2 days while the recovery period is assumed to be 5 days, resulting in the serial interval to be 7 days.[7] Thus, in this disease outbreak, the effect of any government intervention will be seen only after this 7-day period is over. To account for this time-lag and to also extricate the noise from the daily incidence data, the past 7-day average value of β is being used as a covariate. Further, to change the range of R_i from [0,1] to $(-\infty,\infty)$, its log-odds ratio is being used in the model. All SEIR fitted β_i vary between 0 and 1, thus using its log-odds provides a statistical advantage. Additionally, this is a zero-intercept Gamma model.

Table 3.Strictness of Phases of Un-lockdown

Phase	Start	End	Value of
Before lockdown	02-Mar	24-Mar	0.00
Lockdown 1.0	25-Mar	14-Apr	0.99
Lockdown 2.0	15-Apr	03-May	0.95
Lockdown 3.0	04-May	17-May	0.90
Lockdown 4.0	18-May	31-May	0.80
Unlock 1.0	01-June	30-June	0.60
Unlock 2.0	01-July	31-July	0.50
Unlock 3.0	01-Aug	31-Aug	0.40
Unlock 4.0	01-Sept	30-Sept	0.30
Unlock 5.0	01-Oct	31-Oct	0.20

Each phase of the lockdown has been assigned a specific "strictness" rating. The following table (Table 3) represents the phase-wise R_j.

On running multiple simulations, an optimal equation for the aforementioned GLM is as follows:

$$\eta_i = \lambda_R \ln\left(\frac{R_i}{1-R_i}\right) + \lambda_A A_i + \lambda_\beta \ln\left(\frac{\overline{\beta^7}_i}{1-\overline{\beta^7}_i}\right) + \epsilon_i$$

Table 4.Results of Model Formulation

Covariate	Estimate	Std. Error	Testing Statistic	p-value
$\ln\left(\frac{R_i}{1-R_i}\right)$	0.272941	0.070134	3.891685	≈ 0
A_i	0.000081	0.000015	5.420075	≈ 0
$\ln\left(\frac{\overline{\beta^7}_i}{1-\overline{\beta^7}_i}\right)$	-2. 582556	0.194153	-13. 301622	≈ 0

An inverse link function is used for this Gamma based GLM, i.e., $\beta_i = {}^1/_{\eta_i}$. The following were the results of the model formulation (Table 4).

As is evinced through the results (Table 4), each parameter is highly significant, thus negating the need to extricate any.

GLM Model Simulation

The fitted values of the Gamma model seem to be following the trend of β_t appropriately (Figure 5). The testing cohort varies from 21st April to 1st September. SEIR fitted values of β_i were available from 2nd March onwards, albeit the initial values were truncated due to the unavailability of data for the covariates, excessive initial sampling error in β, etc. The testing cohort varies from 2nd September to 31st October. The MSE for the testing & testing cohorts were -0.004 and 0.0184. A 99% CI for the difference between the means of the two cohorts is computed to be (-0.046, 0.0009), thus indicating no significant difference between the means of the two sets.

GLM Model Checking

Overfitting can easily be diagnosed using actual-vs-fitted visualisations. The graph below (Figure 6) does not indicate any signs of overfitting. To check for underfitting, the model bias needs to be assessed. This Gamma model is not too strictly regularised, and also allows for a heteroscedastic

Figure 5.Transmission Rate: GLM Fitted vs SEIR Fitted

error distribution. The AIC for the model was computed to be -359.21, while the BIC was calculated to be - 347.61;

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with the Dispersion parameter for Gamma family taken to be 0.074974. All of these factors evince a good fit.

Studying the errors of the model involves the comparison between the "accuracy" (measured against the training set) and the "validation accuracy" (measured against the validation/ testing set). A Welch two-sample t-test returns a p-value ≈ 0. This implies that there is enough evidence

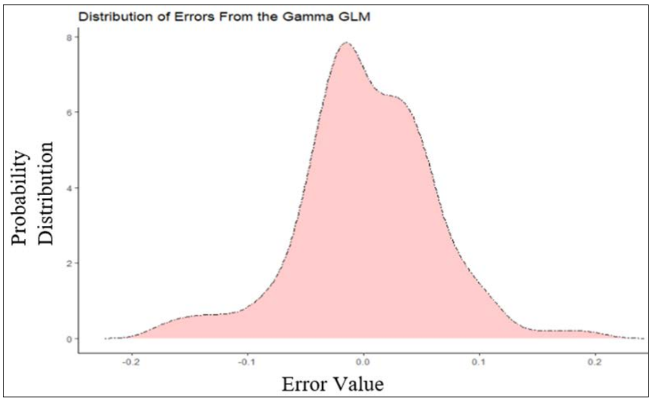

Figure 6.Distribution of Errors from Gamma GLM

to suggest that the means of the training and validation cohorts are significantly different from one another. This is indicative of heteroscedasticity, i.e., the distribution of the error term is non-normal. The 95% non-parametric CI of $\epsilon_i \in$ (-0.137,0.111); with the mean ≈ 0.

An alternative approach to deal with this heteroscedasticity is the application of a weighted least squares methodology, with the errors are treated as weights during the minimisation of the MSE. This methodology was not adopted here due to the response's (β) positive skewness. A Gamma Model with 'log' link function is another alternative to adjust for this skewness.

SEIR β_i vs GLM β_t

Comparison of the distribution of the GLM fitted β_t and SEIR fitted β_i yields the density (distribution) plot (Figure 7).

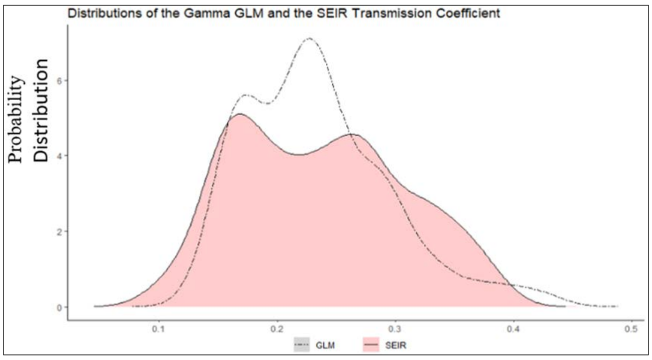

Figure 7.Distribution of Gamma GLM and SEIR Transmission Coefficient

A Welch Two Sample t-test suggests that the GLM fitted β and SEIR β data sets are not significantly different from one another. The test returns a p-value of 0.4617, along with a 95% confidence interval (-0.0162, 0.0102) of the differences between the means of the two samples.

The SEIR Model yields a relatively heavier tail as compared to a Gamma Regression Model. The rationale behind this disparity is the (comparatively) lighter tail of Gamma distribution. A Weibull or Pareto model would be better suited to model the time-dependent transmission coefficient β_t.

Results

The 7 day moving average for β, for the various phases of unlockdown are presented in Figure 2. The value of β continued a downward trajectory, maintaining values below 0.2, for most of the phases of unlockdown, except during two particular phases:

- For most parts of Unlockdown phase I starting from June 1, till June 30, 2020. During this period, the β value stayed between 0.2 and 0.4, having comparable values to the Lockdown period
- During the later part of phase IV and early part of phase V (which were panning later and early parts of the months of August and September of the year 2020) (Figure 2)

One sample t test performed for the error (actual-fitted) of SEIR model provided evidence for the true mean being not significantly different from the empirical mean (Figure 3). The results of GLM model were also checked by testing for the difference between the means of the two cohorts, which was found to be statistically insignificant (Figure 6). Further, overfitting of the model was ruled out with visualisation, while AIC and BIC values were ruled out underfitting. The MSE for the testing & testing cohorts was calculated and the 99% CI for the difference between the means of the two cohorts is computed to be (-0.046,0.0009), thus indicating no significant difference between the means of the two sets.

Discussion

Various parts of India are again seeing a rise in COVID-19 cases, and many countries including India have already faced multiple waves of the pandemic. This makes it all the more important for us to critically analyse the public health interventions employed in the mitigation of the pandemic.

Considering the emergence of new strains of SARS-CoV-2 virus, which are more infectious and difficult to be managed by the treatment modalities developed so far, it is possible that governments all over the world will again have to resort to strategies like lockdown again. Thus, our paper helps in two ways:

1. Drastic measures like lockdown are important but cannot be a feasible long-term measure. Thus, it is important to understand if the reversal of the same, that is unlockdown, can be done, without compromising

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the public health needs. Our paper provides evidence on the same.

2. Our paper also provides an insight into the trends of disease transmission during different phases of the un-lockdown. This can inform policy-makers about the activities that potentially contribute to increased disease transmission, and thus should be carefully controlled and monitored when resumed.

Lockdown had provided very clear medical benefits by restricting public movement and thus reducing transmission of the disease. This opportunity was also taken by the government to upscale its healthcare infrastructure, expand testing and extensively trace all the available cases. But the longer we extended this lockdown, the more difficult it became for the economy to survive. Thus, there was a need for the reversal of lockdown. This was perhaps an even more difficult decision, considering reversal or unlockdown was going to increase the risk of exposure to the susceptible population. This was going to be problematic for two obvious reasons 1. Overall burden of infection of COVID-19 (number of cases and deaths) was going to increase 2. The risk of putting a strain on the economy during lockdown would have been a big waste. Thus, to retain the benefits of the lockdown, and to make sure

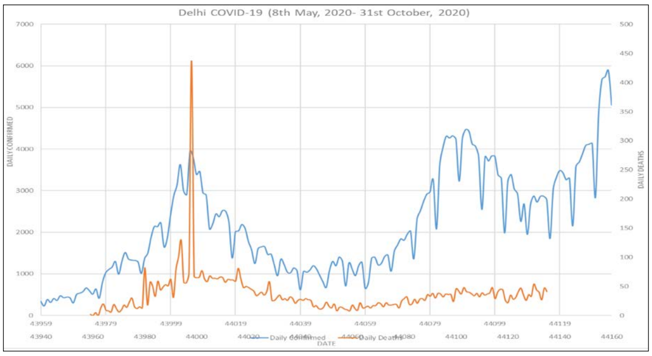

Figure 8.Daily Confirmed Cases and Daily Confirmed Deaths in Delhi

the anticipated increase in caseload does not cripple the healthcare infrastructure, the unlockdown was done in a phased manner - resumption of activities in a phased manner over several months, based on the importance of nature of activities.

Containment strategy, that is the creation of containment zones in high-risk areas instead of an area-wide lockdown, continued to stay in place. Gradual increase in the proportion of staff required for working in various public and private institutions and very careful need-based resumption of public transport was undertaken. Meanwhile, expansion of the healthcare facilities and infrastructure, in terms of extensive testing, isolation strategies and medical treatment continued to tackle the anticipated increase in the number of COVID-19 cases. In our paper, we have proved that this phased unlockdown in fact managed to achieve what it set out to resumption of the activities to a near-normal state, while ensuring decreased transmission of disease.

The analysis of general trend of daily number of new cases and daily new deaths (Figure 8), makes it obvious that the number of cases and deaths both kept an upward trend during the phases of lockdown. This can be attributed to the fact the testing capacity and reporting of the covid related statistics was continuously improving. Thus to account for this variance in detection and reporting, and to get a true picture of the spread of the pandemic, we looked at the transmission coefficient β.

The overall trend of the values of β during various phases of lockdown was a downward slope (Figure 2). This means that while the absolute number of cases and deaths due to COVID-19 infection was increasing, the transmission of the infection, on the whole, was decreasing. This can be attributed to various factors like:

- Use of precautionary measures like masks, hand hygiene, social distancing and observance of cough etiquettes
- Early identification and prompt isolation of new cases, resulting in the potential reduction of risk of exposure to healthy individuals from these cases
- Improved availability of effective medical treatments for COVID-19 infection, which considerably decreased the period of illness as well as the number of deaths

A phase-wise analysis of values of β can help us better understand the effect of resumption of specific activities on the transmission of the disease. Soon after the lockdown ended, that is, on 01/06/2020, β remained comparable to the lockdown period. It was towards the end of the month of June (26/06/2020) that β started a downward trajectory. The value of β during this period being comparable to the value of β during lockdown shows that un-lockdown was done timely and did not worsen the spread of infection. Afterwards, the trend was overall a downward slope, except during two periods, as discussed earlier, the values of β increased. The first augmentation in the transmission rate was seen during phase I of unlockdown (Figure 2). This increase in the rate of transmission can be explained by the fact that this was the initial phase of unlockdown - From June 8th shopping malls, religious places, hotels and restaurants reopened (Table 1). This meant a sudden increase in the number of people getting exposed to the infection, and also more people getting themselves tested for the infection. But it is noteworthy that the rate of transmission remained comparable to the lockdown phase. Thus, the unlockdown during this phase did not worsen the spread of the pandemic.

Second upward slope was seen during the latter half of

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phase IV and the first half of phase V. During this time, three major activities were resumed (Table 1). Delhi metro rails, Public gatherings were allowed with a cap on the number of people allowed and swimming pools were reopened. Delhi metro rail is a widely used public transport system. The metro rail system, the stations and train bogeys are enclosed spaces, making the entire period of commute for the passenger a period of high risk for exposure. Though the entry points of all the metro stations had a system for temperature screening, urged passengers to observe precautions, ensured social distancing in the metro stations and trains, and performed periodic sanitisation of the stations and trains, the enclosed system of transport carrying multiple people at a time probably increased their exposure to the infection. Similarly, permitting gatherings, though of a limited number of people and while ensuring all measures of precautions, still enabled transmission of infection to multiple people from a single source. Swimming pools could have increased the risk of exposure by allowing direct contamination of the water body by an infected individual, which other healthy people came in contact with. All these three activities have one thing in common the risk of transmission of infection is high from a single source to multiple people at a given time. All these could have contributed to the high rate of transmission and thus high values of β during this period. These findings have direct implications on policy making:

1. Phased unlockdown was, epidemiologically speaking, a successful strategy. It enabled the retention of the benefits of lockdown as the upscaling of infrastructure during lockdown and advocacy on precautionary measures against covid infection helped bring the transmission rate down during the unlockdown period.
2. Activities that increase the risk of transmission of infection from a point source to multiple people in enclosed spaces should be carefully monitored to prevent flaring up of the pandemic. It will be thus interesting to the effect of reopening of academic institutions on the spread of the pandemic.

Rationale for using β instead of R_t

Though conventionally Rt or daily reproduction numbers (Reproduction number of an infection is the expected number of cases directly generated by one case in a population where all individuals are susceptible to infection) are used to quantify the spread of the epidemic,[8-14] there is no consensus on the method that gives most accurate measurements for Rt. The root of this discordance lies in the assumptions of various models used for its calculation. SEIR model, a widely used model for Rt calculation uses the four sets of differential equations given above to indirectly determine Rt using various mathematical approaches.[4] However, let us try to understand what variables affect the transition between these classes of SEIR individually.

1. A person moving from a class of susceptible individuals to exposed will be affected by various public health interventions that reduce his exposure, namely lockdown, social distancing and precautionary measures like wearing a mask. Thus, lockdown and un-lockdown will have the most significant effect on this transition of an individual from S to E.
2. A person, when exposed will get infected based on two factors mostly - his degree of exposure (quantum of virus particles) and his immunity. These two affect the transition of an individual from E to I.
3. Once infected, the medical interventions available - like isolation, early testing and treatment and an array of treatment options available will affect the person's transition from I to R, which is removed. Also, the number of individuals infected at a given time will affect the transmission co-efficient β.

Since Rt calculation takes into consideration all these transitions, it is difficult to determine which variable - the public health interventions, the immunity or the medical interventions, has the most effect on its fluctuation. This limitation is overcome by using β, the transmission coefficient. β governs the transition from S to E, which in turn is affected by public health interventions and the number of active cases at a given time, and thus can serve as a good indicator to study the effect of public health intervention.

The phase-wise beta values calculated from the conventional SEIR model incorporate the effect of all the public health interventions, though it is difficult to calculate the effect of each intervention separately from the underlying model. Therefore, a Generalised Linear Model has been designed to statistically assess the significant contributions of each intervention.

β vs R_t

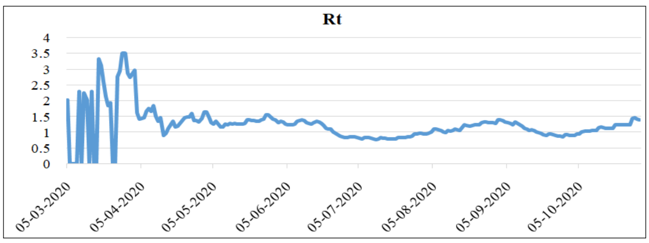

Figure 9.Time-dependent Reproduction Number (Rt) Values for Delhi

Rt values have been calculated for Indian settings using an inbuilt function given in software R (version Rx 64.3.6.3), "est.R0.TD".[15] We used the same approach to calculate Rt. Now to compare the two, β and R_t as measures of temporal spread we present the graph of the two values - β (Figure

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2) and R_t (Figure 9).

As is evident empirically from the graphs, the time of the rise and fall in R_t (above and below the threshold i.e. 1) is similar to the rise and fall in β. This shows that the timing of increase in the spread of the epidemic can be captured as well as by β, as it is captured by R_t.

Conclusion

Through this paper, we provide evidence that un-lockdown can be achieved without increasing the transmission of disease disproportionately. Thus, a phased wise approach to un-lockdown is encouraged. We also provide empirical evidence for activities that can potentially lead to increased disease transmission and thus should be strictly monitored and controlled during the un-lockdown. Finally, we provide the rationale for using β over R_t values to specifically assess the effect of public health interventions designed to decrease exposure, and empirically show that the results obtained by using Rt values and β values are comparable.

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