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Forecasting the patterns of COVID-19 and Causal Impacts of Lockdown in Top Ten Affected Countries using Bayesian Structural Time Series Models

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Highlights

- Forecasts for the future patterns of COVID-19 in top five affected countries
- Causal impacts of lockdowns in the top five affected countries
- Improved forecasts under Bayesian Structural Time Series Models
- Investigation of trend, seasonality and regression components separately
Forecasting the patterns of COVID-19 and Causal Impacts of Lockdown in Top Ten Affected Countries using Bayesian Structural Time Series Models

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Abstract:

Background: There are numerous studies dealing with analysis for the future patterns of COVID-19 in different countries using conventional time series models. This study aims to provide more flexible analytical framework that decomposes the important components of the time series, incorporates the prior information, and captures the evolving nature of model parameters.

Methods: We have employed the Bayesian structural time series (BSTS) models to investigate the temporal dynamics of COVID-19 in top five affected countries around the world in the time window March 1, 2020 to June 29, 2020. In addition, we have analyzed the casual impact of lockdown in these countries using intervention analysis under BSTS models.

Results: We achieved better levels of accuracy as compared to ARIMA models. The forecasts for the next 30 days suggest that India, Brazil, USA, Russia and UK are expected to have 101.42%, 85.85%, 46.73%, 32.50% and 15.17% increase in number of confirmed cases, respectively. On the other hand, there is a chance of 70.32%, 52.54%, 45.65%, 19.29% and 18.23% growth in the death figures for India, Brazil, Russia, USA and UK, respectively. In addition, USA and UK have made quite sagacious choices for lifting/relaxing the lockdowns. However, the pace of outbreak has significantly increased in Brazil, India and Russia after easing the lockdowns.

Conclusion: On the whole, the Indian and Brazilian healthcare system is likely to be seriously overburdened in the next month. Though USA and Russia have managed to cut down the rates of positive cases, but serious efforts will be required to keep these momentum on. On the other hand, UK has been successful in flattening their outbreak trajectories.

Keywords: posterior probabilities, intervention analysis, prediction intervals and forecast accuracy measures.

Introduction

Year 2019 ended with a start of an historical pandemic named novel corona virus or COVID-19 by the World Health Organization (WHO, 2020). This pandemic was started in Wuhan, China, during December, 2019 (Paules et al., 2020). It escalated at drastic pace and covered almost the whole world till March, 2020 (WHO, 2020). The COVID-19 is the seventh number of coronavirus family that can affect humans (D. Hui et al., 2020). The WHO declared it as pandemic on 11th March, 2020 (WHO, 2020). Although the COVID-19 has low mortality rates as compared to severe acute respiratory syndrome (SARS) and Middle East respiratory syndrome (MERS), this virus has higher transmissibility (Tomar and Gupta, 2020). Since the patterns of COVID-19 are not known and its end is also uncertain, the repeated quantitative analysis of its patterns is fundamental (Li et al., 2020; Zhou et al., 2020 and Wang and Zhang, 2020). The short term forecasts can provide the stakeholders some important hints to formulate their strategies to tackle the evolving scenarios (Ippolito et al., 2020 and McCloskey et al., 2020).
There are numerous studies dealing with future patterns of this pandemic in different countries. For example in Pakistan (Yousaf, et al., 2020), Iran (Moftakhar et al., 2020), India (Gupta and Pal, 2020), Germany, Turkey and France (Yonar et al., 2020) and for world data (Benvenuto et al., 2020). However, these contributions have employed the conventional methods, such as static regression and ARIMA models, to forecast the future behavior of this pandemic. Unfortunately, these models have certain limitations. The static regression models follow the deterministic way to model the time series as the sum of components (trend, seasonal and irregular) for analysis. These models also assume that pattern of time series is steady over time, which is seldom true. On the other hand, the forecasts under ARIMA models depend on the previous patterns of the series along with preceding forecasting errors. These models also encounter the issue of over-fitting, especially in presence of covariates (Brockwell and Davis, 2002).

As an alternative approach, the Bayesian structural time series (BSTS) models, due to Brodersen et al. (2015) and Scott and Varian (2013), have some appealing advantages. These models let the model parameters change over time, can handle large number of predictors and accurately reveal the stochastic behavior of the time series (Harvey, 1989). The Bayesian approach allows us to impose prior information on the variables. These models can be efficiently used in public health for prioritizing, developing and implementing policies to tackle and avoid the adverse health situations (Scott and Varian, 2014). These models have already been used to forecast the health damages due to use of alcohol (McQuire et al, 2019) and to forecast the health harms and crime rates as a results of local alcohol licensing policies (de Vocht et al., 2017). It is also possible to select the suitable variables via Spike and Slab priors using these models (Poyser, 2019). The BSTS models produced 14% improvement in forecasts regarding consumer sentiment (Scott and Varian, 2014). The BSTS models produced better forecasts, as compared to ARIMA, for future heath harms due to use of alcohol. They produced reasonably good 1-5 year forecast, even with only eight data points in the training dataset (McQuire et al, 2019).

In short, the BSTS models are the stochastic state-space models that can investigate the trend, seasonality and regression components separately. These models consider spike and slab prior for selection of optimal covariates and Bayesian model averaging is used to produce the final forecasts. The forecasts from these models are least dependent on certain hypothesized specifications. Using these models, the model factors are automatically weighted based on their inclusion probabilities. These models select the most informative parameters and do not require the linear regression component of the model. These models provide improved representation of the certainty of estimates, and evolve (embitter their accuracy) over time (McQuire et al, 2019). However, the analytical computation of the Bayesian posterior distribution is extremely difficult. So, the numerical computations are carried out using Markov Chain Monte Carlo (MCMC) methods such as Gibbs sampling (George and McCulloch, 1997). The recently developed bsts package in R is used to employ the Bayesian structural time series (BSTS) models (Scott, 2020).

Since strict lockdown in Wuhan helped China to prevent the outbreak of COVID-19 in other provinces (Li et al., 2020), the assessment of impacts of lifting/relaxing the lockdowns in the targeted countries can be very interesting. The causal impacts of lockdown in these countries can be analyzed using intervention analysis. The intervention analysis using BSTS models are used to measure the impact of intervention in the post intervention period. In converse to conventional linear models, these models measure the evolving impact in terms of dynamic confidence interval for the difference between inherent and counterfactual observations. This chronological process along with some other advantages such as, incorporation of prior information and complex covariate structure makes these models superior to the conventional models (Liu et al. 2020).

We have planned this study to investigate the temporal dynamics of the COVID-19 in top five affected countries around the globe. These countries include USA, Brazil, Russia, India and UK. We have also investigated the causal impacts of the lockdown imposed in these countries. To achieve this purpose, we have considered BSTS models and
intervention analysis under BSTS models. The results provided improved accuracy as compared to those under ARIMA models. The proposed methodology can be employed to analyze these trends in any other countries.

Methodology

We have obtained the data from the published reports of Our World in Data (Our World in Data, 2020) and HDX (HDX, 2020). These data includes the number of new confirmed cases, cumulative confirmed cases, new deaths, cumulative deaths, new recoveries cumulative recoveries, new tests, cumulative recoveries along with some other details. Since we have used the published data, no ethical approval is required for the study.

We have compared the results under ARIMA and BSTS Models using variety of forecast accuracy measures such root mean square error (RMSE), mean absolute error (MAE), root mean square percentage error (RMSPE) and root median square percentage error (RMdSPE). These forecast accuracy criteria suggest that the Bayesian methods can be efficiently used in forecasting the patterns of this pandemic. This approach develops the analytical models based on prior experience and data at hand (likelihood function). The prior distribution can incorporated in the shape of expert opinion and likelihood function includes the patent data regarding the current patterns. The prior information is combined with likelihood function to update the information that results into final Bayesian model called posterior distribution. This distribution is estimated using Gibbs sampling (George and Mcculloch, 1997). The most recently introduced bsts package, in R, has been used to run the Bayesian structural time series (BSTS) models (Scott, 2020). This package uses spike and slab prior for the regression component of the models and Kalman filter for the time series component. The usual Bayesian dynamic linear models require variables to be Gaussian. The BSTS models have the capacity to incorporate the non-Gaussian variables. One additional advantage of the BSTS models is that we can visualize the trend, seasonal and regression components of the model (Scott, 2020). In addition, the causal impacts of lifting/relaxing the lockdowns have been analyzed using intervention analysis under BSTS models. The numerical results for the causal impacts have been obtained using CausalImpact package in R (Brodersen and Hauser, 2020).

Results and Discussions

We have conducted the study to investigate the future behavior of COVID-19 in top five affected countries and to observe the causal impact of lifting/relaxing lockdown in these countries. As of June 29, 2020, USA conceded 2,548,996 confirmed cases, 125,804 deaths and 705,203 recoveries. Brazil with speedy outbreak reached 1,344,143 positive cases, 57,622 deaths and 757,781 recoveries. Russia currently ranked third, with respect to COVID-19 cases in the world, witnessed 634,437 confirmed cases, 9,073 deaths and 402,778 recovered cases. India is also facing serious growth in the outbreak with 548,318 positive cases, 16,475 deaths and 334,822 recoveries. Similarly, UK has reached 311,151 positive cases and 43,550 deaths. Unfortunately, the temporal data regarding number of recoveries in UK is unavailable. Having these data at hand, our first task was to compare the forecasting accuracy of the proposed BSTS models and most frequently used ARIMA models. This comparison has been reported based on different measures of forecasts accuracy such as RMSE, MAE, RMSPE and RMdSPE. The results regarding comparison of forecasting accuracy are presented in Table 1. Similarly, the forecasts for next thirty days and expected required number of crucial care beds and ventilators have been given in Table 2 and in Figure 1. The investigation of trend, seasonality and regression components is given in Figure 2. Finally the causal impacts of lifting/relaxing lockdowns have been reported in Table 3 and in Figure 3 presented in Appendix A.

| Countries | Item      | Results under BSTS Models | Results under ARIMA Models |
|-----------|-----------|---------------------------|---------------------------|
| USA       | Cases     | 3874 2948 0.0498 0.0029   | 4391 2980 0.0491 0.0032   |
|           | Deaths    | 414 442 0.0579 0.0051     | 431 250 0.0686 0.0056     |
The comparison among BSTS models and ARIMA models, in terms of different measures of forecast accuracy, has been reported in Table 1. The results regarding forecasts for recoveries in UK have not been reported due to unavailability of the data. These results revealed that the BSTS models produced more accurate forecasts as compared to those under ARIMA models. There are few exceptions, may be due to random behavior of the data. Hence, BSTS models proved to be an appealing alternative to ARIMA models for forecasting the patterns of COVID-19 in these countries. Therefore, we have reported the details of the forecasts only under the BSTS models.

Table 2 reports one month ahead forecasts for the top five affected countries. On July 29, 2020, USA is expected to have 46.73%, 19.29% and 38.53% increases in total number positive cases, deaths, and recoveries, respectively. As the percentage increase in number of positive cases is expected to remain higher than percentage increase in recoveries, the healthcare system of the country is have to bear more burden in the next month. According WHO estimates, 15% of the COVID-19 patients carry severe infections needing crucial care and 5% of the patients require ventilator (WHO, 2020). Hence USA will require (for next thirty days) 391,970 crucial care beds and 130,657 ventilators for 2,613,132 active cases in the country. The forecasted figures for Brazil are quite alarming. The country is likely to have 85.83%, 52.54% and 73.77% rises in total number positive cases, deaths and recoveries, respectively. The healthcare infrastructure in the country is expected to be seriously overburdened in the coming month. For 1,093,045 active cases, the country will require 163,957 crucial care beds and 54,652 ventilators. Similarly, Russia will also see the increasing trends of COVID-19 in the next month. The total number of confirmed cases, deaths and recoveries are prone to increase by 32.50%, 52.54% and 55.34%, respectively. The good news for the country is that the rate of increase in the recoveries can be higher than the rate of increase in the total positive cases and bad news is that the death toll can increase rapidly. With these forecasts the country will require 30,265

| Country | No. of expected cases | No. of expected deaths | No. of expected recoveries | No. of active cases | No. of required crucial care beds | No. of required ventilators |
|---------|------------------------|------------------------|---------------------------|---------------------|-------------------------------|---------------------------|
| USA     | 3740088 (3321153,4189029) | 150074 (128612,184866)  | 976683 (801178, 1178258)  | 2613132             | 391970                        | 130657                    |
| Brazil  | 2497760 (2219824,2827922) | 87896 (79045, 96586)   | 1316818 (762717, 1834970) | 1093045             | 163957                        | 54652                     |
| Russia  | 840665 (725233, 956212)   | 13215 (11450, 14920)   | 625684 (527384, 723555)   | 201767              | 30265                         | 10088                     |
| India   | 1104404 (1001880, 218441) | 28061 (20122, 36893)   | 709763 (613982, 807100)   | 366580              | 54987                         | 18329                     |
| UK      | 358365 (321188, 405949)   | 51491 (45862, 59619)   | --                         | --                  | --                            | --                        |

Table 2 reports one month ahead forecasts for the top five affected countries. On July 29, 2020, USA is expected to have 46.73%, 19.29% and 38.53% increases in total number positive cases, deaths and recoveries, respectively. As the percentage increase in number of positive cases is expected to remain higher than percentage increase in recoveries, the healthcare system of the country is have to bear more burden in the next month. According WHO estimates, 15% of the COVID-19 patients carry severe infections needing crucial care and 5% of the patients require ventilator (WHO, 2020). Hence USA will require (for next thirty days) 391,970 crucial care beds and 130,657 ventilators for 2,613,132 active cases in the country. The forecasted figures for Brazil are quite alarming. The country is likely to have 85.83%, 52.54% and 73.77% rises in total number positive cases, deaths and recoveries, respectively. The healthcare infrastructure in the country is expected to be seriously overburdened in the coming month. For 1,093,045 active cases, the country will require 163,957 crucial care beds and 54,652 ventilators. Similarly, Russia will also see the increasing trends of COVID-19 in the next month. The total number of confirmed cases, deaths and recoveries are prone to increase by 32.50%, 52.54% and 55.34%, respectively. The good news for the country is that the rate of increase in the recoveries can be higher than the rate of increase in the total positive cases and bad news is that the death toll can increase rapidly. With these forecasts the country will require 30,265
crucial care beds and 10,088 ventilators for next thirty days. India is expected to have 101.42%, 70.32% and 111.98% increases in total number of positive cases, deaths and recoveries, respectively. Though the number cases in the country will grow at much high pace, the recoveries will increase at even higher trajectory. However, the number of expected deaths can really tease the country. Alongside, the country is expected to achieve third rank in the COVID-19 affected countries. According to our forecast, the country will need 54,987 crucial care beds and 18,329 ventilators for the next month. Unfortunately, we were unable to report complete figures for UK, as the historical data regarding recoveries in the country were not available. Nonetheless, the total number of confirmed cases and deaths are expected to rise at slower rate, as compared to other countries in the top five ranks. The country will face 15.17% and 18.23% increases in the total number of confirmed cases and deaths. Hence, the top four COVID-19 affected countries are likely to continue facing hard times against the pandemic. On the other hand, UK has quite flattened the trajectory of the pandemic in the country. Hopefully, the country carry on to further control the outbreak in coming months.
Figure 1: Forecasts for total number of positive cases, deaths and recoveries for top five COVID-19 affected countries.
One of the advantages of using BSTS models is that we can investigate the contribution of trend, seasonality and regression separately using these models. We have analyzed these patterns in our case. The contributions of these components have only been reported for total number of confirmed cases in the targeted countries. The patterns for other parameters were of the similar kind, hence not reported for brevity. We have considered the number of cumulated tests conducted by each country as covariate, because the number of total positive cases depends on the total number of tests conducted. The details have been reported in Figure 2. The results for USA elucidate that trend of total number of cases is increasing almost linearly since April, 2020. The seasonal effect is even over time. The curve of regression component is decreasing. Therefore, the ratio of positive cases to number of total tests is decreasing since April, 2020, which is good sign for the country. On the other hand, Brazil is witnessing the exponential growth in total number of cases. The contribution of seasonality was absent till May, 2020 and started expanding thereafter. The rate of number of cases with respect to number of tests is mounting after April, 2020. This can cause serious issues for the country in coming months. As far as the Russia is concerned, there is serious escalation in number of positive cases since mid April, 2020. The effect of seasonality is steady over time. However, the country has managed to cut down the rate of positive cases since start of April, 2020. For India, the number of positive cases and rate of positive cases are increasing exponentially since start of May, 2020. The country may face turmoil of positive cases in the next month. However, the temporal impact of seasonality is random in the country. Unfortunately, the historical data regarding number tests conducted by UK were unavailable up to March 31, 2020. Hence we have obtained the results starting from April 1, 2020. Interestingly, UK has managed to flatten the trajectory of positive cases and rate of positive cases. The seasonal contribution was only visible during April, 2020. To sum up the above discussion, we can say that healthcare infrastructure in Brazil and India is expected to be overburdened in the coming month. These countries need to mobilize additional resources to meet the needs of coming months. USA and Russia should keep on reducing the rate of positive cases and they should also try to flatten pace of growing cases. UK has already restricted the pace of confirmed cases and rate of cases is also decreasing over time. We should hope that UK may set trends for other countries striving against this pandemic.

Our next target was to observe the causal impact of lifting the lockdowns in the top five affected countries. It should be noted that USA has relaxed the lockdown in different phases and most effective release took place on June 13, 2020. In Brazil the lockdown start easing on April 20, 2020. Russia chosen to left the strict lockdown on April 30, 2020. India started the fifth phase of lockdown with significant relaxation on May 31, 2020 (Wikipedia, May 29, 2020). The prime minister of UK announced to reduce the lockdown restrictions on May 10, 2020 (The Guardian, May 10, 2020). These lockdown lifting/relaxing dates have been used as intervention while doing the intervention analysis under BSTS models. We compared the currents figures with expected figures, had the lockdowns not lifted in these countries. The validity of the results has been investigated in terms of posterior probabilities and probability of causal impacts. The results have been reported in Table 3, and in Figure 3, given in the Appendix A. We can see that posterior probabilities of having these effects as random events are too small. On the other hand, the probabilities of causal impacts are quite high. This simply indicates the significance of the causal impacts of lifting/relaxing lockdown in all the top five affected countries. The lifting/relaxing of lockdown has increased the
number of cases in Brazil, Russia and India by 86%, 39% and 29%, respectively. These countries also encountered the increase in their death counts with 34%, 17% and 3.8% for Russia, Brazil and India, respectively. So, these countries may not have precisely chosen the time for the lifting/relaxing of the lockdowns. On the other hand, in USA and UK, there is not visible impact of relaxing the lockdowns. The currents figures, for total number of cases and total number of deaths, are even less than those expected during the full lockdown. Hence, these countries have made better choices of relaxing the lockdowns.

Table-03: Effect of lifting lockdown in top five countries

| Country | Item  | Actual Figure | Expected Figure | Absolute effect | Relative Effect | Post. Prob. | Prob. of Causal Impact |
|---------|-------|---------------|-----------------|-----------------|-----------------|------------|------------------------|
| USA     | Cases | 2548996       | 2331530         | -217466 (468099, 150004) | -8.70% (-19%, 0.6%) | 0.001      | 99.90%                |
|         | Deaths| 125804        | 112402          | -13402 (-21611, -5579) | -10% (-16%, -4.5%) | 0.001      | 99.90%                |
| Brazil  | Cases | 1344143       | 1124143         | 220000 (190000, 260000) | -86% (73%, 99%)  | 0.001      | 99.89%                |
|         | Deaths| 57622         | 53821           | 3801 (241, 7045) | -17% (1%, 32%)  | 0.020      | 98.00%                |
| Russia  | Cases | 634437        | 525582          | 108855 (82286, 133324) | 39% (30%, 48%)   | 0.001      | 99.90%                |
|         | Deaths| 9073          | 7884            | 1189 (897, 1470) | 34% (26%, 42%)  | 0.001      | 99.90%                |
| India   | Cases | 548318        | 471340          | 76978 (5992, 92460) | 29% (22%, 35%)  | 0.001      | 99.90%                |
|         | Deaths| 16475         | 16094           | 381 (80, 999) | 3.80% (1.3%, 9.9%) | 0.030      | 97.00%                |
| UK      | Cases | 311151        | 611151          | -30000 (-400000, -250000) | -55% (-68%, -44%) | 0.001      | 99.88%                |
|         | Deaths| 43550         | 44453           | -903 (-1247, -32) | -8.60% (-16%, -1.2%) | 0.012      | 98.73%                |

Conclusion

A careful review of literature suggests that no study has involved the differentiation of the elements that have considered the evolving behavior of the COVID-19 patterns. The important aspect of the study is that the BSTS models disaggregate the COVID-19 patterns into different components. The proposed approach also allows the coefficients to vary with time in order detect the data generation process in more detail. We demonstrated that BSTS models provide effective support in timely planning, prioritizing and allocating the healthcare resources in mitigating the harms of COVID-19 in the countries under study. In addition, the causal impacts of lifting/relaxing the lockdowns have been investigated. The findings of the study suggest that forecasting accuracy of the proposed models is better as compare to frequently used ARIMA models, with few exceptions. Except UK, the top five affected countries are expected to encounter serious growth in number of positive cases during next month. The ranks for the percentage increase in total number of cases will be India > Brazil > USA > Russia > UK. The numbers of deaths are expected to increase at very high rate in India, Brazil and Russia as compared to those expected in USA and UK. In this case, the percentage increase will follow the following order India > Brazil > Russia > USA > UK. Finally in terms of expected increase in percentage of recoveries, these countries will be in following sequence India > Brazil > Russia > USA. The percentage increase in number of cases is expected to higher than number of recoveries in USA and Brazil. In additions, the ratio of positive cases to the number of tests conducted is growing in Brazil and India, which can cause more trouble to these countries in coming month. Our analysis also reveals that USA and UK have chosen quite suitable patterns for lifting/relaxing the lockdowns. On the
other hand, the easing of lockdown has increased the trajectory of the outbreak in Brazil, Russia and India. These countries may revisit strategies towards the lockdowns. To sum up the above discussion, we can say that UK has been able to manage the outbreak quite effectively; however the country should also prepare the data regarding recoveries. USA and Russia have been successful in cutting down the rate of positive cases, but they are still far away from the safety lines. However, for next thirty days, the situation can be more complicated in Brazil and India. We believe that these findings will be beneficial for these countries in effectively prioritizing, developing and implementing their strategies to reduce the expected harms of this pandemic.

This study has some limitation as well. We have assumed that the data obtained is correct; however these can be under reported as not all the patients report themselves to hospitals and some of the patients are asymptomatic. Due to unavailability of corresponding data, no risk factors have been investigated. Though BSTS models provided improved forecasts as compared to ARIMA models, still embedded uncertainty in the data may affect the accuracy of these forecasts. However, the purpose of the study is not to provide hundred percent true forecasts, but to provide the stakeholders some important signals to plan their strategies accordingly.

Declaration of interests

☐ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Appendix-A: Causal Impacts of lifting/relaxing lockdowns in top five affected countries

| No. of cumulative cases and deaths in USA | No. of cumulative cases and deaths in Brazil |
|-----------------------------------------|------------------------------------------|
| ![Graph](image1.png)                    | ![Graph](image2.png)                    |

| No. of cumulative cases and deaths in Russia | No. of cumulative cases and deaths in India |
|--------------------------------------------|--------------------------------------------|
| ![Graph](image3.png)                      | ![Graph](image4.png)                      |
Figure 3: Analysis for causal impacts of lifting/relaxing lockdowns in the top five affected countries