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Regime shifts in the COVID-19 case fatality rate dynamics: A Markov-switching autoregressive model analysis

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A B S T R A C T

The 2019 novel coronavirus disease (COVID-19) has spread rapidly to many countries around the world from Wuhan, the capital of China’s Hubei province since December 2019. It has now a huge effect on the global economy. As of 13 September 2020, more than 28, 802, 775, and 920, 931 people are infected and dead, respectively. The mortality of COVID-19 infections is increasing as the number of infections increase. Many countries published control measures to contain its spread. Even though there are many drugs and vaccines under trial by pharmaceutical companies and research groups, no specific vaccine or drug has yet been found. Therefore, it is necessary to explain the behaviour of the case fatality rate (CFR) of COVID-19 using the most updated COVID-19 epidemiological data before 13 September 2020. The dynamics in the CFR were analyzed using the Markov-switching autoregressive (MSAR) models. Results showed that the two-regime and three-regime MSAR approach better captured the non-linear dynamics in the CFR time series data for each of the top heavily infected countries including the world. The results also showed that rises in CFRs are more volatile than drops. We believe that this information can be useful for the government to establish appropriate policies in a timely manner.

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1. Introduction

A local outbreak of pneumonia named the Coronavirus Infectious Disease (COVID)-19 discovered in Wuhan, China in December 2019 and has spread quickly to many countries around the world. The disease is caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), which had not previously been identified in humans. It may spread from bats to humans through another intermediate host [1,2]. The World Health Organisation (WHO) declared the outbreak as a Public Health Emergency of International Concern on January 30, 2020, [2]. The WHO also declared this virus as a global pandemic on March 11, 2020 [3].

As of 10:26 am CEST, 13 September 2020, more than 200 countries have been affected with more than 28, 802, 775 COVID-19 cases worldwide with the maximum being in the United States of America (USA) (6, 386, 832) followed by 4, 754, 356 in India, 4, 282, 164 in Brazil, 1, 057, 362 in Russia and 716, 670 in Peru. The overall global case fatality rate (CFR) is 3.21% (Fig. 1). The CFR has differed from country to country on multiple parameters such as population demographics, factual reporting, healthcare delivery, number of tests performed, etc. [4]. More to the point, among the world’s top 10 countries with the number of confirmed COVID-19 cases, the highest CFR was recorded in Mexico with 10.66% and the lowest CFR was recorded in India with 1.65% (Fig. 1). As of 13 September 2020, South Africa has the highest number of infections and deaths in Africa.

The CFR fluctuations in the time series data (in global and in some heavily infected countries such as the USA, India, Brazil, Russia, and Peru) can be seen in Fig. 2. As shown in Fig. 2, the time series is irregular. The CFR was high globally between the middle of April and the middle of May. Furthermore, there was a sharp decline in June and July and a sharp rise at the beginning of August (Fig. 2a). Similar to the global CFR case, the CFR in the USA was high in May, June, and the beginning of August (Fig. 2b). The CFR of Brazil was also in the rising state in June and July and in the declining state at the beginning of August (Fig. 2c). Moreover, there is a positive trend of CFR globally, also in the USA, Brazil, India, and Peru in the first few months, indicating that CFR is increasing. Therefore, this huge rise and fall of CFRs call for further research.

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investigation. In other words, it is important to understand the dynamic properties of CFRs globally and the top 5 heavily infected countries in the world.

Timely and precise information on CFR dynamics is needed to monitor the global ups and downs of the types observed over the last seven months. Several studies have been focused on different aspects. (i) Forecasting the epidemic trends in COVID-19 in different countries like USA, Brazil, Russia, India, and the United Kingdom [2], China [5,6], Italy [7], Pakistan [8], most affected countries [9] and so on. (ii) Comprehensive review of responses to COVID-19 [4,10,11]. (iii) the biological and epidemiological overview of COVID-19 including the SARS-2 coronavirus [1,13]. (iv) Case reports [14,15] and so on.

However, in this research, we revisit the issue of modelling and forecasting CFR time series data with the Markov-switching autoregressive (MSAR) model. This model offers rich dynamics to model the CFR time series data. It incorporates the fluctuations and structural breaks in the dynamic behaviour of CFR data [16]. It has been applied by Shumway and Stoffer [17] to model monthly pneumonia and influenza deaths.

Having this in mind, the aim of this research is twofold. First, the primary aim is to analyze the dynamics of CFR over time. To gain a better understanding of the dynamic properties of CFRs, highly infected countries such as the USA, India, Brazil, Russia, and Peru along with the global case were identified and analyzed using the MSAR model. Second, this paper provides one-step-ahead forecasting of the CFR in the top five heavily infected countries including the world. To evaluate the quality of the forecast, we employed statistical metrics including mean square error (MSE) and mean absolute error (MAE).

2. Material and methods

2.1. Data description

In this paper, we focus on the cumulative daily time series figures globally and the top 5 countries with the highest number of infections in the world. These data were extracted from the WHO COVID-19 Dashboard (https://covid19.who.int/table accessed on 13 September 2020) covering the period (Global: 1/12/2020 – 9/13/2020; USA: 3/3/2020 – 9/13/2020; Brazil: 3/18/2020 – 9/13/2020; India: 3/13/2020 – 9/13/2020; Russia: 3/26/2020 – 9/13/2020 and Peru: 3/7/2020 – 9/13/2020).

2.2. Calculating case fatality rate

The CFR was calculated as the ratio between the number of confirmed deaths from disease and the total number of confirmed cases with the disease:

\[
\text{Case Fatality Rate (CFR, in %)} = \frac{\text{Number of confirmed deaths}}{\text{Number of confirmed cases}} \times 100
\]

In this study, the CFR of COVID-19 infections on 13 September 2020 was calculated by dividing the number of confirmed deaths on 13 September 2020 by the total number of confirmed cases on 13 September 2020 for each respective country [18]. Figure 2 shows a plot of daily CFR over time. It is also evident from Fig. 2 that there are trends in the data. To fit the MSAR model to these data sets, we should remove the trend [17]. The log-differenced data, \( y_t = (\log CFR_t - \log CFR_{t-1}) \), where CFR is the

![Fig. 1. The world’s top 10 countries with the number of confirmed COVID-19 cases.](https://covid19.who.int/table)
CFR at time $t$ and $CFR_{t-1}$, the CFR at time $t - 1$ is shown in Fig. 3. As shown in this figure we are successful in removing the trend.

2.3. Methods

This section describes the methods employed in this work. Let the change in the CFR at time $t$ be $y_t$, for $t = 1, \ldots, T$. In general, Markov-switching models divide the time series into different regimes that are called states or regimes. In this research, we define separate and independent underlying CFR processes for each regime. This study focuses on the Markov-switching autoregressive models of the form (see [19])

$$y_t - \mu_{S_t} = \sum_{m=1}^{p} \phi_{m,S_t} (y_{t-m} - \mu_{S_{t-m}}) + \sigma_{S_t} \epsilon_t,$$  

(1)

where $\mu_{S_t} = \sum_{i=1}^{r} \mu^{(i)} I(S_t = i)$ and $\phi_{m,S_t} = \sum_{i=1}^{r} \phi^{(i)} \phi_{m}(S_t = i)$, $m = 1, \ldots, p$ are the dependent parameters: $\sigma_{S_t} = \sum_{i=1}^{r} \sigma^{(i)} I(S_t = i)$ is the state dependent variance; $\epsilon_t$ is an independent, identically distributed (i.i.d.) random variable with zero mean and variance $1$. Here $\mu^{(i)}, \sigma^{(i)}$ and $\phi_{m}(i = 1, \ldots, r)$ are real constants, and $m$ is a positive integer. According to Psaradakis and Spagnolo [19], the model defined by Eq. (1) can be thought of as an $r$-state $m$-order Markov-switching autoregressive [MSAR($r,m$)] model.

This research uses the unobservable discrete-regime (state) Markov process to generate $S_t$ [20]. In this study $S_t = 1, 2, \ldots, r$ is a first-order unobservable Markov process with transition matrix $P$ as follows:

$$P = (P_{ij})_{1 \leq i, j \leq r},$$  

(2)

where $P_{ij} = P(S_t = j | S_{t-1} = i)$ denotes the probability of switching from Regime $i$ (starting regime) at time $t - 1$ to Regime $j$ (landing regime) at time $t$, and $\sum_{j=1}^{r} p_{ij} = 1$. For example, $p_{11}$ and $p_{22}$ denote the probabilities of staying in Regime 1 and Regime 2, respectively.

The conditional density of $y_t$ is assumed to be: $f(y_t | y_{t-1}; \Theta)$, where $\Theta$ is a vector of parameters to be estimated. In MS modelling, the task of the analyst is to estimate the parameter vector $\Theta$ given a time series observations of the data. The unknown MS model parameter $\Theta$ can be estimated using the logarithmic likelihood function given as

$$L(\Theta) = \sum_{t=1}^{T} \ln f(y_t | y_{t-1}; \Theta).$$  

(3)

To test the presence of regime-switching in the time series CFR, we may test the hypothesis of the form: $H_0$: non-switching model, versus $H_1$: regime-switching model. The above hypotheses are tested using the likelihood ratio (LR) statistic given as [21]:

$$LR = 2[L(\hat{\Theta}) - L(\hat{\Theta}_0)],$$  

(4)

where $\hat{\Theta}$ and $\hat{\Theta}_0$ are the maximum likelihood estimators for $\Theta$ and $\Theta_0$ under $H_1$ and $H_0$, respectively.

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**Fig. 2.** The daily case fatality rate (%) in Global (a), USA (b), Brazil (c), India (d), Russia (e), and Peru (f) by 10:26am CEST, 13 September 2020.
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Fig. 3. Log returns of the daily CFR in Global (a), USA (b), Brazil (c), India (d), Russia (e), and Peru (f) by 10:26am CEST, 13 September 2020.

The Bayesian Information Criterion (BIC) [22] was employed to select an appropriate specification. Recall that

\[ BIC = m \log(T) - 2 \log L, \tag{5} \]

where \( L \) is the likelihood function and \( m \) represents the number of parameters included in the chosen model. Smaller BIC values indicate a better model.

2.4. Forecast evaluation

Lastly, the standard statistical measures such as MSE and MAE were used as forecasting performance of the different MSAR\((r,m)\) models. The MSE and MAE were calculated using Eqs. (6) and (7) (see [23])

\[ MSE = \frac{1}{N} \sum_{t=1}^{N} (y_t - y_t^{pred})^2, \tag{6} \]

\[ MAE = \frac{1}{N} \sum_{t=1}^{N} \left| \frac{y_t - y_t^{pred}}{y_t} \right|, \tag{7} \]

where \( y_t \) = actual CFR time series data; and \( y_t^{pred} \) = forecasting outcome.

Table 1
LR test statistics for determining the presence of regime in the time series CFR data.

|       | Global | USA   | Brazil | India  | Russia | Peru  |
|-------|--------|-------|--------|--------|--------|-------|
| LR    | 737.72 | 394.12| 177.76 | 345.46 | 280.38 | 89.74 |

3. Results

3.1. Modelling the dynamics of CFR in global and in the top five heavily infected countries in the world

Table 1 reported the LR statistic for the time series CFR in the global and top five heavily infected countries. Since the LR statistic was greater than the \( \chi^2 \) - distribution with two and three degrees of freedom (i.e. \( X_{0.05}^2(2) = 5.992; X_{0.05}^2(3) = 7.815 \)), we rejected \( H_0 \). Thus, there was strong evidence of the presence of regime-switching, which made the use of regime-switching regression models justifiable.

The MSAR models were fitted with a number of regimes \( r \) varying from 1 to 5 and the order of autoregressive models varying from \( m = 1 \) to \( m = 3 \). Table 2 presents the BIC values for the different MSAR models. As shown in this table, the BIC values suggest optimal models with \( r = 3 \) and \( m = 3 \) for Brazil, Russia and Peru; \( r = 3 \) and \( m = 2 \) for global; \( r = 2 \) and \( m = 3 \) for USA and \( r = 3 \) and \( m = 2 \) for India. We observe that there is a big improvement in
the BIC values when \( r \) increases from 1 to 2 and from 2 to 3. We noticed that the BIC values are generally increasing when \( r > 3 \).

Finally, we fitted MSAR(3,3) model for Brazil, Russia and Peru; MSAR(3,2) model for Global, MSAR(2,3) for USA and MSAR(3,2) for India for the entire period. Parameter estimates are displayed in Table 3. For global case as an example, the standard deviations \( \sigma_1 = 0.053, \sigma_2 = 0.007 \) and \( \sigma_3 = 0.608 \) for regime 1, regime 2 and regime 3 respectively. For USA \( \mu_2 > \mu_1 \) and \( \sigma_2 > \sigma_1 \), which indicates that regime 2 as a “null state” of high volatility and of regime 1 as a “bear state” also characterized by lower volatility.

For global case as an example, the transition probabilities \((p_{11}, p_{22}, p_{33}) = (0.948, 0.955, 0.868)\) indicate that the states corresponding to \( S_1 = 1 \) and \( S_2 = 2 \) are equally persistent and much more so than the regime corresponding to \( S_3 = 3 \) [19].

Figure 4 shows the smoothed probabilities in the two-regime and three-regime MSAR models for CFR. The blue, red, and green lines represent the estimated probabilities of regime 1, regime 2, and regime 3 respectively. We can observe the regime at every moment and its duration using the smoothed probabilities [24]. From this figure, we can easily observe that the regimes are radically different. For example, the CFRs of India and Peru show the frequent regime shifts since the beginning of August.

Figure 5 shows observed CFR returns and conditional mean from the fitted MSAR models, with all regimes, delineated reasonably well. Furthermore, Figure 6 shows the plots of residuals versus fitted values. From this plot, it is apparent that the assumption of constant variance is reasonably met.

### 3.2. One step ahead forecasting of the case fatality rate in global

Table 4 summarizes the forecasting errors measured by MSE and MAE for comparing the one step ahead forecasting performance of the MSAR models. In short, we compare the prediction accuracy of the MSAR models when \( r > 1 \) and \( m > 1 \) against the
Table 4
Comparisons of forecasting performances of different MSAR models.

| Countries | r  | 1   | 2   | 3   | 4   | 5   | 1   | 2   | 3   | 4   | 5   |
|-----------|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
|           |    | MSE |     |     |     |     | MAE |     |     |     |     |
| Global    | 1  | 49.285 | 49.185 | 45.123 | 42.202 | 69.656 | 68.322 | 69.076 | 66.574 | 70.809 |
|           | 2  | 37.555 | 79.292 | 67.219 | 43.704 | 40.697 | 61.436 | 83.890 | 75.494 | 62.970 | 65.753 |
|           | 3  | 33.908 | 52.894 | 39.079 | 13.920 | 24.050 | 58.830 | 65.051 | 61.090 | 45.022 | 53.993 |
|           | 4  | 1.006 | 0.006 | 0.005 | 0.010 | 0.005 | 0.795 | 0.797 | 0.795 | 1.001 | 0.776 |
| USA       | 1  | 0.005 | 0.005 | 0.004 | 0.005 | 0.006 | 0.813 | 0.761 | 0.738 | 1.015 | 0.834 |
|           | 2  | 0.004 | 0.005 | 0.004 | 0.004 | 0.006 | 0.780 | 0.725 | 0.721 | 0.697 | 0.934 |
| India     | 1  | 36.613 | 37.208 | 37.888 | 38.594 | 73.739 | 71.020 | 71.800 | 75.229 | 75.313 |
|           | 2  | 26.122 | 26.039 | 26.499 | 24.728 | 31.062 | 62.015 | 57.810 | 55.935 | 46.545 | 71.857 |
|           | 3  | 25.160 | 26.222 | 26.170 | 25.729 | 33.363 | 58.972 | 57.935 | 56.646 | 54.345 | 75.201 |
| Brazil    | 1  | 16.351 | 16.331 | 16.070 | 16.323 | 14.370 | 60.618 | 59.465 | 58.659 | 58.346 | 57.053 |
|           | 2  | 13.859 | 14.481 | 15.726 | 13.967 | 14.814 | 59.286 | 59.176 | 59.219 | 56.693 | 57.681 |
| Russia    | 1  | 0.701 | 0.451 | 0.499 | 0.587 | 0.571 | 12.064 | 12.160 | 11.006 | 11.211 | 10.889 |
|           | 2  | 0.552 | 0.741 | 0.542 | 0.529 | 0.381 | 11.275 | 12.323 | 10.304 | 10.230 | 9.769 |
| Peru      | 1  | 39.654 | 39.748 | 38.637 | 36.926 | 35.474 | 85.685 | 84.557 | 85.365 | 81.576 | 78.525 |
|           | 2  | 39.524 | 39.375 | 37.529 | 38.019 | 39.747 | 85.742 | 84.858 | 84.635 | 85.113 | 86.162 |

Fig. 4. Probabilities of observations being in different regimes for Global (a), USA (b), Brazil (c), India (d), Russia (e), and Peru (f) by 13 September, 2020.

4. Discussion

The world is currently impacted by the COVID-19 pandemic. It is the latest threat to face mankind which might take more than a decade for the world to recover economically [12]. Despite containment efforts, as of 13 September 2020, the CFRs in the USA, reference model ($MSAR(1,1) = AR(1)$). The $MSAR(4,3)$ model was selected as the best for forecasting the global and USA CFR. The $MSAR(5,2)$ model was selected as the best for forecasting the Peru CFR. It is observable that the $MSAR(4,2)$ and $MSAR(2,3)$ models were the best models in forecasting the Indian and Brazilian CFRs respectively.
Brazil, India, Russia, and Peru were 3.01%, 3.05%, 1.65%, 1.75%, and 4.25%, respectively and there are still a daily rising deaths.

Even though the current COVID-19 pandemic is an international health problem, comparisons of CFR between countries can be problematic [25]. Due to this reason, we analyzed the CFRs of the global and top five heavily infected countries using MSAR models. Given the dynamic behaviour of CFR, applying the MS model with dynamic autoregressive coefficients can be a promising approach. The proposed model allows consecutive CFR jumps that are important when dealing with risk management. The dynamic process was introduced through the addition of lagged values of the dependent variable. The non-linear evolvement of the CFR time series is analyzed through regime-switching governed by a discrete-state Markov process. BIC was used to determine the optimal number of regimes.

The daily CFR recordings were utilized to validate the capability of the MS model in the CFR forecasting. Different CFR forecasting approaches, MS process with \((r = 1, 2, 3, 4, 5)\) states and AR dynamics with \((m = 1, 2, 3)\) lags were introduced as baselines in the one step ahead point forecast of CFRs.

Fig. 5. CFR returns and conditional mean of the fitted MSAR models for Global (a), USA (b), Brazil (c), India (d), Russia (e), and Peru (f) by 13 September, 2020.
As shown in Table 3, for USA as an example, $\hat{\mu}_1 < \hat{\mu}_2$ and $\hat{\sigma}_1 < \hat{\sigma}_2$, which means that regime 1 is the falling state with low volatility while regime 2 is the rising state with high volatility. An interesting finding of applications of MSAR(r,m) models to CFR time series is that most coefficients are statistically significant. It indicates that CFRs are generally serially correlated except for a few particular regimes. For instance, the estimated AR parameters of the CFRs of Brazil are $(\phi_{13} = 0.031), (\phi_{23} = -0.106)$ and $(\phi_{33} = 0.721)$. It means that the CFRs of Brazil are highly and positively serially correlated with a lag of three days data in rising and falling periods but rather negatively serially correlated with a lag of three days data in the relatively stable periods. Similarly, for the USA case, the estimates of the AR parameters are $\phi_{11} = 0.544, \phi_{13} = 0.212, \phi_{13} = 0.114, \phi_{21} = 0.190, \phi_{22} = 0.028, \phi_{23} = 0.489$, which indicates that the USA CFR is positively correlated with the previous day’s data.

Furthermore, as shown in Fig. 3, there were three regimes in the time series of CFRs of global, India, Brazil, Russia, and Peru, which can be called the “rising”, “relatively stable” and “falling” regimes. However, there were two regimes in the time series of CFR of the USA, which can be called the “rising” and “falling” regimes. The CFRs of USA frequently stayed in the “rising” regime until the middle of May, although they were often in the sharply “falling” regime around the 20th of May, in the rising regime in between June and July; in the falling regime in between July and August. The CFRs of Brazil were in the sharply rising regime from June to August, which burden hospitals far beyond their management capacity [2]. However, they were more or less stable up to June, and sharply “falling” since the beginning of August. The CFRs of India were in the “rising” regime until the beginning of August, frequent regime shifts from the middle of August to the present.

For instance, the estimated transition probability of USA $p_{11} = 0.969$, which is the probability to remain in regime 1 in the next day given it is regime 1, while the probability to transition from regime 1 to regime 2 in the next day is $1 - 0.969 = 0.031$. Furthermore, the average number of days that regime 1, regime 2 and regime 3 persist is given as $(1 - p_{11})^{-1}, (1 - p_{22})^{-1}$ and $(1 - p_{33})^{-1}$, respectively [26]. Table 5 reported the average duration of the three regimes of CFRs for global, Brazil, India, Russia, and Peru; and two regimes for the USA. It can be seen that the “falling” regime dominated the sample period for global, USA and India. The “relatively stable” regime was also dominated by Brazil.

![Fig. 6. Residuals versus fitted values for Global (a), USA (b), India (c), Brazil (d), Russia (e), and Peru (f) by 13 September, 2020.](image-url)
Russia, and Peru CFRs. For example, the global CFRs have experienced volatile movements, their main trends proved downward in a significant manner.

Forecasting plays a vital role in managing the risk associated with COVID-19 [2,6,7]. However, the prediction of infectious disease patterns has been a challenging task since the spread of the disease is a dynamic process driven by many biological and social factors like networks of social contacts, travel, infectiousness, etc. [27]. Even though infectious disease prediction was a challenging task, there are studies in the literature. For example, [28] used a resampling technique to forecast the peak of seasonal influenza outbreaks in the USA. Recently, [2] applied a machine learning approach along with a logistic model to predict the epidemic trends in COVID-19. In our case, the MSAR models ($r > 1$ and $m > 1$) outperformed the reference model (AR(1)), expressing the smallest error variance.

5. Conclusion

Up to the date of writing of this paper, the number of infections and deaths continue to rise in more than 200 countries worldwide. This pandemic presents a major shock and global panic, also causing the worst economic crises in 30 years [29]. This paper deals with the development of the MSAR model to study the dynamics of CFRs of COVID-19 from the top five most affected countries namely the USA, Brazil, India, Russia, and Peru including the world. The analysis offers useful information about the dynamics of CFRs of COVID in the world and the top five heavily infected countries.

Lastly, the main results that emerged from this research can be concluded as follows.

1. The results indicated that the CFRs are strongly regime-dependent. The three-regime MSAR model overall provides more accurate in-sample estimation results for global, India, Brazil, Russia and Peru. Meanwhile, the two-regime MSAR model outperformed the results of the rest of the MSAR models for the CFRs of the USA.

2. In terms of prediction, the four-regime MSAR model overall provides more accurate one-step ahead forecasting for the global, USA and Indian CFRs, while the five-regime MSAR model provides higher predictive accuracy for the Russian and Peru CFRs forecast. The two-regime MSAR model provides more accurate predictive accuracy for the Brazilian CFR forecast. In general, the regime-switching model overall performs better than the single regime AR(1) model.

This research used univariate CFRs to model and forecast daily changes in CFRs of the top heavily infected countries including the world. Future areas of work may include exploring CFRs along with other factors such as positive cases, recovery rate, etc. with multivariate methods.

Declaration of Competing Interest

The author declares that he has no conflict of interest.

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