COVID-19: did preventive restrictions work?

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During the ongoing COVID-19 pandemic, if a preventive restriction (PR) intended to arrest transmission of the virus is effective, we expect a decrease in the rate of transmission. If an effective PR is lifted or relaxed, the reverse is expected. We test this expectation in the history of PR imposition and relaxation in all countries based on available public database using a null model of spontaneous change in the rate of transmission independent of PRs. We use the stringency index defined earlier and available in public database to represent PR in different countries at different times. We found no negative correlation between standing stringency index of PR and change in slope of the local curve. A change in stringency index was significantly negatively correlated with change in slope, but it could explain only 6.1% of the variance in rates of transmission. The distribution of slope changes after imposing versus after relaxing PRs was highly overlapping with only a tail consisting of 4.5% PR impositions being clearly non-overlapping with PR relaxation. Non-parametrically, only 5.9% of PR impositions were associated with a reduction in the slope above the expectation of a null hypothesis. Globally, PRs have played a small role in the pandemic up to March 2021. This feedback needs to be considered in making policies for disease prevention in the further course of the COVID-19 pandemic as well as in any future threats of respiratory disease epidemics.

Keywords: COVID-19, epidemiology, lockdown, preventive restrictions, stringency index.

DURING the ongoing pandemic of COVID-19, non-pharmaceutical interventions (NPIs) for prevention of transmission have been implemented at an unprecedented global scale. Whether and to what extent these preventive measures worked is difficult to answer. In the first phase of the epidemic several studies estimated the effect of various NPIs; some of them found the interventions to be quite effective[1–4] while others reported limited, inadequate or disappointing effects[5–7]. Regarding specific measures such as school closures, different studies have widely different findings[8,9]. The constraints on data in the first phase posed many difficulties in making an unbiased estimate. In any of these studies, there was no control group to compare with, which was an inevitable limitation. Some studies were based on patterns in a single country[2,5,10,11], while others compared selected countries but did not explicitly specify the inclusion and exclusion criteria for the countries selected[3,4,6,12,13]; however, one study used global data[1]. A major hurdle in comparative analysis across countries is that many other variables differ substantially between countries, making a fair comparison difficult and possibly misleading. For example, it is apparent that countries with better healthcare infrastructure have higher death rates[14], which is counterintuitive; but such a pattern may be observed because of other confounding variables. Therefore, comparison across countries has limited reliability. Some studies considered reduction in an index such as prevalence or rate of transmission at the same location as the measure of effectiveness of the intervention[4,6,7,11]; however, they do not control for possibility of spontaneous changes in rates independent of preventive measures. Most studies suffer from a lack of appropriate null model. Given the multiple hurdles in estimating the efficiency of an intervention, a robust conclusion has been difficult. Moreover, all the studies used data from the early phase of the pandemic. One year period up to March 2021, the context in terms of population immunity, viral variants, Government strategies, and people's response has changed substantially. Therefore, a reanalysis is required using data over the above-mentioned period.

The NPIs have two distinct components from the implementation point of view. Some of the measures are imposed by the Governments, which we call preventive restrictions (PRs). Others such as personal hygiene are to be practised by individuals and for which imposition is difficult. While PRs are easy to quantify based on official Government policies, personal protection measures are not. We employed a novel approach to assess the effects of PRs on the time trend in incidence on a global scale using countries as units. To minimize biases, we avoided comparing countries or groups of countries. Instead we considered the change in intrinsic rate of transmission associated with imposition and relaxation of PRs in the same country. If a PR measure is applied at a given point in time, after an expected lag, the slope of the logarithm of daily cases or daily deaths should decrease if the PRs were effective. On the other hand, if the PRs were partially or fully lifted, the slope is expected to increase over that prior to the action (Figure 1). We correlated the standing stringency or the change in stringency index at a given time with the subsequent change in slope for every country in the pooled global data. In the course of an epidemic, the slope also changes naturally in the absence of any intervention. However, if the spontaneous changes are assumed to be independent of PRs, they will not contribute to the correlation. This consideration appropriately incorporates the requirement of a null model of spontaneous change independent of PRs. By this approach, although it is difficult to state whether a given observed change in slope after a change in stringency is spontaneous or in response to a PR, pooling globally one can

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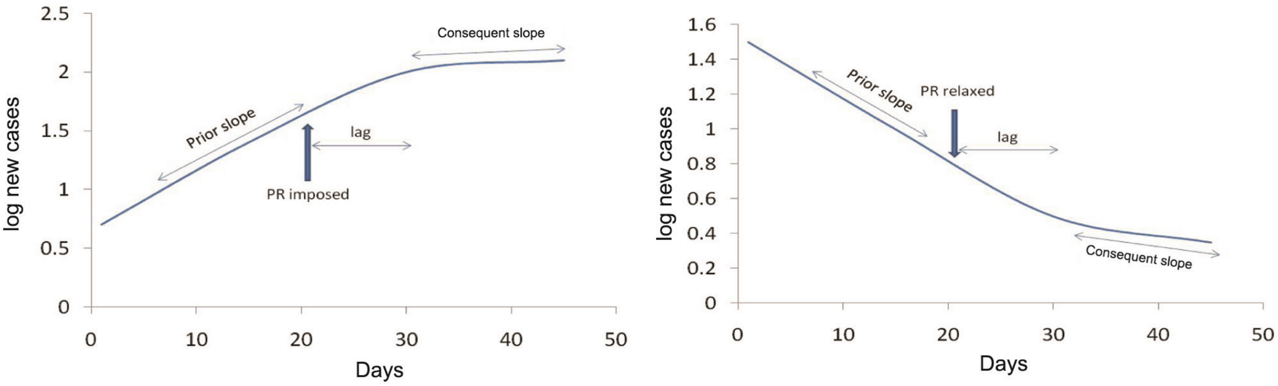

Figure 1. A conceptual diagram showing the expected change in slope of the daily incidence trend by imposing or relaxing preventive restriction (PR) measures. Although in the course of an epidemic, the slope may change spontaneously, if PRs are important determinants of the slope, we expect significant correlation between a change in stringency level of PR and change in the slope associated with it.

estimate whether and to what extent a change in stringency is correlated to a change in the intrinsic growth rate. If a change in the expected direction is not observed with a frequency significantly greater than the possible spontaneous change, PRs are considered to be ineffective. The significance can be checked parametrically as well as non-parametrically. We tested the population-level effect of PRs using this principle, followed by a sensitivity analysis where the assumptions were challenged, the possible biases and confounding were estimated, and it was assessed whether the observed pattern was contributed by the possible biases.

We used a public database (https://ourworldindata.org/coronavirus-data) for time trends in the daily reported number of cases as well as the number of deaths assigned to COVID-19. The stringency index of PRs are available in the database, which is a composite measure based on Hale *et al*.[15] consisting of nine response indicators, including school closures, levels of workplace closures and travel bans, rescaled to a value from 0 to 100 (100 = strictest). The limitation of this index is that the same measures can have different effects in different contexts and different phases of the pandemic[16]. We therefore used a method of analysis to minimize the effect of this limitation by avoiding primary cross-country comparison. For any country we used data from the day when 100 or more cases and/or ten or more deaths were reported per day, and data up to 27 March 2021 were used for analysis. On these criteria we could use data on 731 PR impositions and 724 relaxation events, which were treated as independent of the approach used.

An increase in stringency index corresponds to imposition of a new PR measure, while a decrease corresponds to relaxing or lifting PR. We took the regression slope of eight days prior to the change as the prior slope, then assumed a log of n days for the effect of the PR change and calculated the regression slope of 8, 11 or 15 following days as the consequent slope. Since there is no clear estimate of lag time, we used log of 5, 8, 11, 14 and 17 days for analysis. The difference between consequent slope and prior slope was correlated with the standing level of stringency and the change in stringency. A strong negative correlation was expected if PRs were effective in reducing transmission. We also used the coefficient of determination, R^2 to estimate what proportion of the changes in slope was explained by imposing or lifting PRs. Using two indices of PR, namely standing stringency and change in stringency and trends in two indicators of the effect, namely daily number of cases and number of deaths, also using three intervals for calculating consequent slope and five different lag periods, we selected for further analysis the parameter combination that gave the strongest negative correlation. The selected set of parameters was $n = 14$, consequent slope over 11 days, change in stringency level and daily number of cases. The standing stringency level showed only marginal or non-significant correlation with the associated change in slope (Figure 2 *a*). Trends by daily number of cases and number of deaths did not differ substantially, but correlation of change in stringency using the number of cases was slightly stronger than the number of deaths. Therefore, we used the daily new cases data for further analysis.

For the combination of parameters giving the strongest negative correlation, change in stringency was statistically highly significant ($r = 0.247$, $n = 1455$, $P < 0.0001$), but still a poor predictor of change in slope. It explained only 6.1% variance in the changes in slope (Figure 2 *b*). Thus, over 93% of the course of the pandemic did not appear to be influenced by PRs.

Pooling all impositions and all relaxations together, we observed that the distribution of change in slope after imposition and relaxation of PRs was highly overlapping with only a marginal shift leftwards by imposing restrictions (Figure 3). If we assume that with no effect, the change in slope of the log curve should be zero, the mean change after imposition of PRs was –0.01636, which is equivalent to a 3.8 % reduction in the slope. The difference between the mean change after lifting and imposing

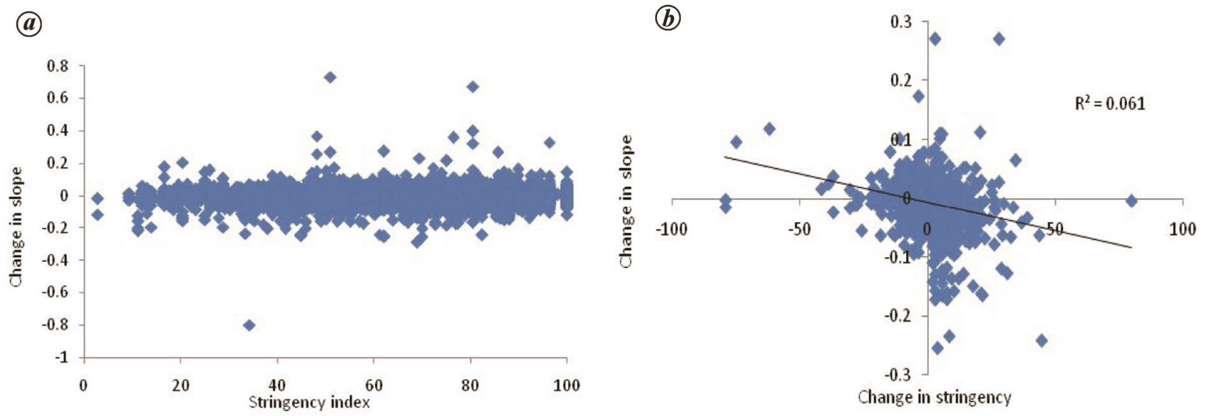

Figure 2. Scatter plots. ***a***, Standing stringency index and the associated change in slope. In this analysis we did not observe the expected correlation between stringency and change in slope. ***b***, Change in stringency, i.e. events of imposing or relaxing restrictions are significantly negatively correlated with slope change, but the variance in slope explained is only 6.1%.

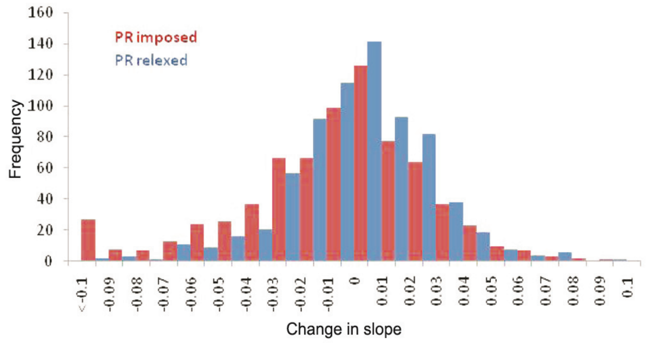

Figure 3. Frequency distribution of slope change in response to imposing PR (red bars) and lifting PR (blue bars). The distribution is surprisingly overlapping, i.e. both imposing and lifting restrictions are followed by positive and negative changes in slope. The modes of distribution lie close to each other. The main difference is in the longish left-hand tail with slope change below –0.1 (being equivalent to over 25% reduction in the rate of transmission) in the distribution after PR imposition, which represents about 3.7% of all PR impositions.

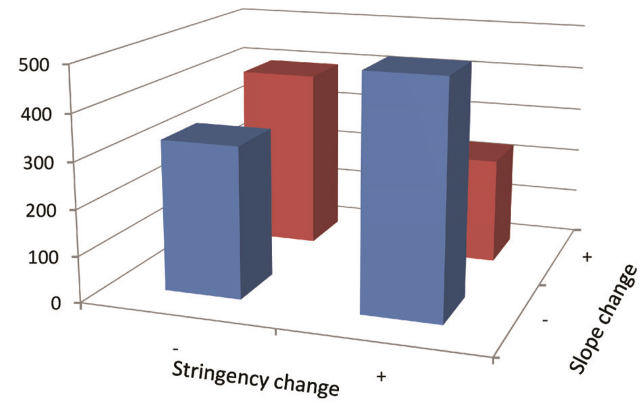

Figure 4. It is expected that imposing PR should reduce the transmission and lifting PR should have the reverse effect. This effect is seen statistically significantly, but a surprisingly large proportion of changes appear to be independent of stringency change.

PRs was –0.0181 equivalent to mean 4.2% change in slope. There was a longish left-hand tail to the PR imposition distribution clearly non-overlapping with the distribution of slopes following PR relaxation, presumably representing the exceptional cases in which PR gave an undoubted and spectacular success. Such clear effective demonstration of the efficiency of PRs was only 27, i.e. 3.7% of the total PRs imposed. Although an increase in stringency is expected to give a negative change in slope, 31% PR impositions resulted into a positive change. Similarly, although lifting of PR was expected to increase the slope, 45.4% of the time, the slope actually decreased.

We observed how frequently a positive change in PR is associated with a negative change in slope, taking a null hypothesis of independence. The effect of change in PR was statistically highly significant ($\chi^2 = 50.54$, $P < 0.0001$), but only 5.9% of PRs lay above what is expected by the null hypothesis (Figure 4).

In brief, we found no evidence that the standing levels of restrictions decreased the rate of transmission, whereas increase in stringency reduced the transmission with statistically significant frequency, but using different statistical tools only between 3.7% and 6.1% of the changes could be accounted for by imposition or relaxation of PRs.

We relaxed our assumptions and checked for possible sources of biases to examine whether the low performance of PRs is a result of one or more sources of bias in the data.

(i) Our analysis is based on the stringency index defined by Hale *et al.*[15] and made available by (https://ourworldindata.org/coronavirus-data). The allocation of importance to the different components of PR is rather subjective and all components are not expected to contribute equally to the effect. Nevertheless, as long as some components are effective, they should have been reflected at least in the non-parametric approach. It is also possible that the stringency index is based on the official declaration of the respective Governments, but the on-ground implementation differs across countries[17,18] as well as with time in a single country owing to seasonality[19] or trends in people's behaviour[20]. However, in this analysis, we did not primarily compare countries with each other. Our primary comparison was with the rate of transmission before and after implementing a PR within the same country. So the stringency index of one country need not be equivalent to that of another. As long as a positive change in stringency brings about a negative change in transmission, our analysis can detect it. For countries where implementation was weak, we can make a limiting assumption that the changes in slope were completely independent of the stringency index. This will certainly create more noise; but as long as the PRs are effective in a sizable number of countries a good correlation is expected. The poor R^2 implies that either PRs proved effective in only a few countries or worked poorly throughout the globe.

(ii) Throughout the data, independent of PRs, we observed a negative correlation between prior slope and slope difference. This is expected by any typical epidemiological model as well. When an epidemic spreads, the rate of transmission reduces gradually. In the global data, taking every day as a unit, there is a strong negative correlation between prior slope and change in slope ($r = -0.81$, $n = 28{,}565$, $P < 0.0001$). Furthermore, PR implementation is more likely when the slope is positive and PR relaxation is more likely when the prior slope is negative. This expected correlation is also evident in the data ($r = 0.097$, $n = 1455$, $P = 0.0002$). Therefore, even if PRs are assumed to have no effect, a negative correlation is expected owing to the combined effect of these two biases. Any attempt to correct this bias would further weaken the observed negative correlation between PRs and transmission rates.

Although we see a statistically significant negative correlation between a change in stringency of PR and change in the slope indicating the rate of transmission, the variance in the rate of transmission explained by PRs is very small. Interestingly, the standing level of stringency did not show a significant correlation with change in the rate of transmission. Further, given the possibility of implementation bias, the apparent magnitude of effect is also questionable, and the true magnitude might be even smaller. Thus, globally the PRs appear to have a statistically significant but small effect on virus transmission.

Our conclusion contrasts many of the early studies that claimed substantial success of the lockdown in many countries[1–4]. This contradiction is likely to be because of multiple factors. Apart from limitations and biases stated in the beginning, there are other possible reasons. An epidemic is a complex process, and the relationship between contact behaviours and viral transmission is likely to be highly nonlinear. An epidemiological model that considers immunity as a continuous rather than a binary variable demonstrates potential nonlinearity and even non-monotonicity in the effects of PRs. Further, the different PRs can have synergistic as well as antagonistic effects with each other[21]. The model also showed that what is effective in the short run can frequently turn counterproductive in the long run. Therefore, the simple assumptions behind PRs may work differently in different contexts. Furthermore, in the first phase when PRs were implemented, the number of infective foci and proportion of asymptomatic cases were smaller. At this stage PRs are more likely to be effective. As the number of undetected and asymptomatic cases increased during the epidemic[22], it might have become more difficult to arrest the transmission. Therefore, although the PRs might have helped in the early phase of the pandemic, they could have lost their efficiency subsequently. Compatible with this possibility we found that among the 27 imposed PRs which resulted in the left-hand tail of Figure 3, 24 were from January to March 2020. It is also possible that because of behavioural and administrative factors, the implementation of restrictions did not remain equally effective in the later phases of the pandemic[17–20]. In the light of this possibility, it is interesting to note that almost all the studies that found the NPIs to be effective were from the early phase of the pandemic[1–4]. It is also possible that our limited and uncertain understanding of the exact mode of transmission may have further limited the design and implementation of effective PR measures[23].

This was the first time in history that PRs were applied on a global scale to reduce viral transmission. The PRs have a large social and economic cost, which some communities can tolerate but others cannot. Therefore, the policy of applying stringent measures for arresting the spread of respiratory infections needs rethinking and evaluating vis-à-vis their social costs in the context of every community. This analysis can be used to design preventive measures in the future course of the COVID-19 pandemic, as well as possible future respiratory disease epidemics.

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Increasing and decreasing trends in extreme annual streamflow in the Godavari catchment, India

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In this study, we present the changing trends in extreme annual streamflow at 38 gauging stations in the Godavari catchment, India, during the period 1966–2015. We have applied Mann–Kendall trend test to the time series of at least 20 years of continuous data. The results indicate an increasing trend in the peak streamflow in the northern stations located within the Wainganga, Wardha and Indravati sub-catchments. We observed a critical declining trend at the upstream, central and downstream of the Godavari main catchment. Increasing trends in annual peak streamflow may cause severe higher magnitude floods in the Godavari catchment in the near future that may affect the lives of millions of population.

Keywords: Flood, gauging stations, peak streamflow, river catchment, trend analysis.

AT the beginning of the 21st century, due to global warming and anthropogenic activities, the increase in flood risks in various parts of the world has been reported[1,2]. India has witnessed several devastating flood events in the past few years that caused colossal damage to the infrastructure, economy and, most importantly, loss of life. Most of the time, floods in the Himalayan foreland and plains are related to heavy precipitation and glacial lake outburst[3,4]. Although severe floods in Peninsular India are primarily triggered by extreme precipitations, the severity and damage depend on both natural and anthropogenic factors[5,6].

The most recent devastating flood event in India was the Rishiganga–Dhauliganga flash flood in Garhwal Himalaya due to rock mass failure that resulted in an avalanche[7]. In 2018, nearly 500 people died and 150 went missing during the Kerala flood due to heavy precipitation and poor management of impoundments[8]. In 2005, Mumbai experienced unprecedented flooding due to heavy precipitation, causing more than 500 fatalities[9].

The Godavari basin is the largest catchment in Peninsular India, comprising an area of ca. 0.3 million km^2 (Supplementary Figure 1). The major geological units of the Godavari are Archean granites, Deccan basalts, Gondwana sedimentary rocks and Quaternary alluvium[10]. Topographically, the Godavari catchment shows great diversity.

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