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Did double lockdown strategy backfire? Cobra effect on containment strategy of COVID-19

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\textbf{A B S T R A C T}

Every citizen responds to governments’ protocols when imposed during a time of crisis. Yet occasionally they counter-react in a way that is not intended by the government, contributing to the cobra effect. The Government of Tamil Nadu, India implemented the double lockdown protocol in the pursuit of restraining the spread of covid-19. Nevertheless, the protocol leads to unanticipated consequences on the spread of novel coronavirus. The thrust of the study is to demonstrate the unprecedented consequences of double lockdown on the growth rate of covid-19 cases, instead of flattening the curve and subsequently reveal the cobra effect on the containment strategy of covid-19. For this purpose, the study adopted an event study methodology to test the effect of the announcement of double lockdown on the spike rate of new covid-19 cases in Tamil Nadu, India. The findings of the longitudinal data analysis revealed a significant increase in covid-19 cases after the government announced a double lockdown. A deeper analysis to determine the factors influencing the abnormal rise in covid-19 cases (CAR) using regression analysis revealed a significant positive effect on population density and a negative impact on ICC and HDI. Until now, no empirical research has evaluated the counter-effects of governments’ protocols in containing a pandemic disease, by adopting an event study approach. Also, this study is the first in the literature to test the theoretical predictions of the cobra effect of the adopted protocol.

1. Introduction

The world is witnessing an outbreak of a novel coronavirus, crossing 34 million-mark in covid-19 cases. The challenge of restraining the spread of the novel coronavirus has become a pressing concern for all nations globally. Consequently, several countries imposed a nationwide lockdown to stop the community spread of covid-19 \cite{1}. Further, many countries implemented several intervening strategies like closing their borders, canceling national and international flights, imposing travel restrictions, closing hotels and public parks to avoid cluster formation \cite{2}. Among all the government protocols adopted, the nationwide lockdown is contemplated as the most crucial move to curb the spread of coronavirus, particularly in countries witnessing a huge population growth. Because, the community spread which is highly plausible in countries with high population density, if started, will have a catastrophic effect on the spread of novel coronavirus. Having said this, India, the fifth most affected country by covid-19, implemented a full lockdown from March 25, 2020. In India, while the Central Government’s full lockdown, with few relaxations, was in enforcement, on April 24, 2020, the state government of Tamil Nadu announced a complete lockdown from April 26, 2020, forbidding shop openings and completely restricting public movement. This is termed as double lockdown, a no relaxation lockdown during a nationwide lockdown \cite{3}. Cobra effect refers to the unintended consequences of a policy, where counter effects of implementing the policy exacerbate the problem rather than curbing it \cite{4}. The term Cobra effect was coined a way back during the time of British rule in colonial India (1858–1947) when the British government announced incentives for every cobra brought dead. Unexpectedly, this policy of the British had a repercussive effect when people started breeding cobras for the greed of money, consequently, increasing the snake population \cite{5}.

The current study attempts to evaluate the effectiveness of the double lockdown strategy against the spread of covid-19 infection using the case of Tamil Nadu. Tamil Nadu, one of the southern states in India is an ideal choice for arguing this case due to a few reasons. First, India is the fifth worst-hit country around the world for this novel corona pandemic. Second, in India, Tamil Nadu is the second most affected state

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by coronavirus. Third, Tamil Nadu is one of the states in India where the double lockdown strategy was implemented. Fourth, all the 37 districts of Tamil Nadu are affected by the novel coronavirus. The aforementioned pieces of evidence bring out an undeniable need for this study to evaluate the effectiveness of the double-lockdown strategy on the spread of novel coronavirus in Tamil Nadu.

The prolonged nationwide lockdown in India has an undesirable impact on the economy, by plunging the GDP by 3.1%. The coronavirus-driven economic recession has pushed millions of people below the poverty line, with a stopping unemployment rate [6]. With minimal welfare safety net provided by the government before imposing a curfew, the lockdown intensified the hardships of millions of migrants and daily-wage workers, where these people were struggling to meet their daily needs of food and medicine, resulting in thousands of hunger deaths [7,8]. This economically costly lockdown strategy implemented by the government should adequately justify its purpose in containing the pandemic [9,10]. Given the prominence in investigating the aftermath effects of imposing an economically costly double lockdown, it is of paramount importance for the study to evaluate whether the adopted measures curbed the spread of the virus or exacerbated the spread, contributing to the cobra effect.

Though several studies have employed event methodology in stock market analysis [11], bitcoin market analysis [12], business research [13] there is scant research in employing event study methodology to test the effectiveness of the governments’ protocol in containing the novel pandemic disease like covid-19. This being the case, the current study substantiates its novelty by addressing the aforementioned gap in the literature. To further emphasize the uniqueness of the study, it was found that so far no empirical research has evaluated the government’s protocol in containing a pandemic disease using an event study approach. Also, this is the first study in the literature to test the theoretical predictions of the cobra effect of the adopted protocol.

The structure of the paper is organized as follows. Section 2 explains the steps followed to conduct event study methodology, section 3 demonstrates the findings of the analysis and section 4 concludes with practical implications.

2. Data and method

An event study is a statistical research methodology that investigates the impact of an event on a company, industry, or economy [14,15]. The current study employs event study methodology to investigate the impact of “Announcement of Double Lockdown” on the surge rate of covid-19 cases w.r.t Tamil Nadu. The following section summarizes the steps undertaken in the current study to meet the research objectives.

2.1. Step 1 - determining the event of interest and unit of observation

The study aims to evaluate the impact of the double lockdown strategy on the spike rate of covid –19 patients in Tamil Nadu. The event of interest under scrutiny is the “Announcement of Double Lockdown in Tamil Nadu”, which happened on 24 April 2020 (t0). The Government of Tamil Nadu announced a complete 4-day lockdown in the state from 26, April 2020 and the announcement were done on 24, April 2020. Consequently, a buying panic was created among the people of Tamil Nadu, due to the fear of an impending shortage of essential commodities, especially food. During this period, covid-19 norms went for a toss in Tamil Nadu. People flouted the social distancing norms by creating clusters in market places (like Koyambedu in Tamil Nadu, India). Therefore, it is certainly plausible that unanticipated panic among people is one of the reasons behind a sudden surge in the spread of novel coronavirus in Tamil Nadu. This premise inspires the study to determine the counter-effects of double lockdown implemented in the state. To examine the effects of the Double Lockdown strategy on the spread covid-19, the study recruits secondary data from a TN public dashboard, stopcorona.tn.gov.in. This website is launched and maintained by the Health and Family Welfare Department of Tamil Nadu and reports timely information on novel corona cases reported in Tamil Nadu. The unit of observation under this study is the number of covid-19 cases, freshly reported daily in the state of Tamil Nadu, which is one of the most affected states in India.

Step 2: Determining the Estimation Period and Event Period

To conduct an event study, it is critical to determine the estimation period (t1 to t2), the period during which an event has no impact on the unit of observation. Moreover, it is inevitable to determine the event period (t3 to t4), during which an event occurs and the unit of observation which eventually has an impact due to the occurrence of the event. The dataset of the research study covers newly reported covid-19 cases during a period of 68 days from 07.03.2020 to 14.05.2020. The event study was conducted on the dataset starting from 8, March 2020 because the rate of change in covid-19 patients is derived only from 8, March 2020 onwards.

So far, there is no standardized method to determine the size of the event window and estimation window. From the extant pieces of literature on event study, it is evident that most of the researchers prefer event window length like 11 days [16,17], 5 days [18,19], 15 days and 21 days [20,21] with the event day (t0) located symmetrically at the center of the event window [22]. Based on this premise, the study reports the results of the T-test for all the commonly used window sizes (Table 1) with 11 days (−5, 5), 5 days (−2, 2), 15 days (−7, 7) and 21 days (−10, 10) respectively.

The estimation period starts from 8, March 2020 and the size of the estimation window varies based on the event size window size. In the event window (−2, 2), the estimation period is 45 days from 08.03.2020 to 21.04.2020. Similarly, for the event window (−5, 5), the estimation size is 42 days, ranging from 08.03.2020 to 18.04.2020 and for the event window (−7, 7), the estimation window size is 40 days (08.03.2020 to 16.04.2020). Finally, the estimation window size is 37 days (08.03.2020 to 13.04.2020) for the event window (−10, 10).

Step 3: Estimating the rate of change in newly reported covid-19 patients

The rate of change in newly reported covid-19 cases for the period 07.03.2020 to 14.05.2020 is determined from the equation below,

\[
ROC(t) = \frac{N_t - N_{t-1}}{N_{t-1}}
\]

where ROC(t) is the rate of change in newly reported covid-19 case at time ‘t’, Nt is the number of freshly reported covid-19 case at time ‘t’ and Nt−1 is the number of freshly reported covid-19 case at time ‘t-1’ i.e. previous day.

The rate of change in newly reported covid-19 reflects a relative change, as previous newly reported covid-19 cases are used as a reference value in estimating ROC(t), unlike relative difference. Hence, the formula for ROC(t) is derived based on the relative change formula, Relative Change (x, x\text{reference}) = \frac{(x - x\text{reference})}{x\text{reference}} = \frac{\Delta}{x\text{reference}}.

Table 1

| Event window | CAR | t- statistic | Significant |
|--------------|-----|-------------|-------------|
| (−2,2)       | 0.783 | 3.967**     | Yes at 1%   |
| (−5,5)       | −0.539 | −2.65**     | Yes at 1%   |
| (−7,7)       | 14.061 | 23.04**     | Yes at 1%   |
| (−10,10)     | 2.043  | 12.675**    | Yes at 1%   |
The rate of change in covid-19 cases is graphically depicted in Fig. 1.

Step 4: Computing the expected rate of change in newly reported covid-19 patients

2.2. Computing the expected rate of change by Mean Adjusted Method

The Mean-adjusted method [23]; Lambertides, 2009) is employed over the estimation period (t1 to t2) to compute the expected rate of change in newly reported covid-19 patients (Fig. 2),

\[ E_{ROC} = \frac{\sum^{T-1}_{t=t1} ROC_t}{t_2 - t_1 + 1} \]

where \( E_{ROC} \) is the expected rate of change in newly reported covid-19 patients, where \( t_1 = -47, t_2 = -3 \) for \((-2,2)\) event window, \( t_2 = -6 \) for \((-5,5)\) event window, \( t_2 = -11 \) for \((-10,10)\) event window and \( t_2 = -8 \) for \((-7,7)\) event window.

2.3. Computing the expected rate of change by GARCH models

The Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) method postulated by Bollerslev [24] is employed in the study to estimate the expected rate of change in newly reported covid-19 patients. GARCH models determine the regression coefficients \( \alpha \) and \( \beta \) by solving the following equation [25] implemented during the estimation period (t1 to t2),

\[ R_t = \alpha + (\beta \times R_{t-1}) + \varepsilon, T \in [t1, t2] \]

where \( \alpha \) and \( \beta \) are regression coefficients, \( \varepsilon \) is the error term.

The three GARCH models differ in the computation of the parameters (\( \alpha \) and \( \beta \)). While GARCH (1, 1) model inflicted non-negative constraints on the parameters (\( \alpha \) and \( \beta \)), E-GARCH (1, 1) model allows negative constraints on the parameters, \( \alpha \) and \( \beta \). Similarly, the GARCH-M (1, 1) model uses conditional standard deviation in computing the expected rate.

For this purpose, the study implemented the three models of GARCH, namely GARCH (1, 1), E-GARCH (1, 1) and GARCH-M (1, 1) in NumXL to determine the regression coefficients \( \alpha \) and \( \beta \). The computed coefficients \( \alpha \) and \( \beta \), using respective GARCH models are employed in the following equation in the event window (t3 to t4) to determine the expected rate of change in newly reported covid-19 cases,

\[ E_{ROC} = \alpha + (\beta \times R_{t}), T \in [t3, t4] \]

where \( E_{ROC} \) is the expected rate of change in newly reported covid-19 patients, where \( t_1 = -47, t_2 = -3 \) for \((-2,2)\) event window, \( t_2 = -6 \) for \((-5,5)\) event window, \( t_2 = -11 \) for \((-10,10)\) event window and \( t_2 = -8 \) for \((-7,7)\) event window.

Step 5: Estimating the Abnormal rate of change in newly reported covid-19 patients

The abnormal rate of change in the newly reported covid-19 is calculated over the event period (t3 to t4) by deducting the expected rate of change from the rate of change in covid-19 cases in the event window. The equation below estimates the abnormal rate of change (\( AR_t \)),

\[ AR_t = ROC_T - E_{ROC}, T \in [t3, t4] \]

Step 6: Testing the Cumulative Abnormal Change Rate in newly reported covid-19 patients

The cumulative abnormal change rate in newly reported covid-19 patients (\( CAR_T \)) is the sum of all the abnormal returns in the event window (t3 to t4) considered in the study.

\[ CAR_T = \sum_{t=t3}^{t4} AR_t \]

To statistically prove that the event of interest (Announcement of double lockdown) has caused an abnormal increase in the number of covid-19 cases, the traditional method of Brown & Warner [23] is implemented to test the following hypothesis.

H0. There is no abnormal cumulative change rate in newly reported covid-19 patients, \( \mu_{CAR} = 0 \)

H1. There is an abnormal cumulative change rate in newly reported covid-19 patients, \( \mu_{CAR} \neq 0 \)

The Traditional T statistic [23] to test the hypothesis is computed as below,

\[ t-value_{car} = \frac{CAR_T}{\text{Std.error}} \]

where Std_error is the standard error which is computed as,

\[ \text{Std.error} = \frac{SD_T}{\sqrt{2 - r + 1}} \]

where SD is the Standard deviation of the number of covid-19 cases in

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**Fig. 1.** Daily records for new covid-19 patients in Tamil Nadu.
the estimation period (t1 to t2).

3. Results of event study

3.1. Findings of the event study using mean-adjusted return method

The study employs an event study methodology to empirically quantify the abnormal spike rate of covid-19 patients in Tamil Nadu due to the announcement of double lockdown on 24, April 2020. Table 2 exhibits the abnormal growth rate of covid-19 patients and the t-statistic for Cumulative abnormal change rate of covid-19 patients, for the post-event period of 21 days ([0,0] to [0,20]). It is empirically evident that there is a significant increase in the covid-19 cases after 3 days from post announcement. The growth rate of covid-19 patients steadily increases from [0, 4] to [0, 18] and it is found to be significant at 1%, as ‘t stat for CAR’ > 2.58.

The study analyzed the impact of double lockdown on the growth rate of covid-19 cases by simulating with various event window sizes (5 days [-2, 2], 11 days [-5, 5], 15 days [-7, 7] and 21 days [10, 10]) and manifested in Table 2. The t-statistic value for 11 days [-5,5], 15 days [-7,7] and 21 days [10,10] infers that there exists a significant impact of double lockdown announcement on the abnormal growth rate of covid-19 cases at 5% level of significance, thus accepting the alternative hypothesis, H1 (μCAR≠0).

3.2. Findings of the event study using GARCH models

Similarly, the study evaluates the catastrophic influence of the double lockdown on the spread of novel coronavirus using event study with the expected rate of change computed by GARCH models, namely GARCH (1,1), E-GARCH (1,1) and GARCH-M (1,1). As observed in Table 3, it is statistically evident that the abnormal rate of change in covid-19 patients, computed using GARCH(1,1) and M-GARCH(1,1) models, shows an increasing trend at 1% significance (t stat for CAR > 2.58) in the post-event period, from [0, 6] to [0, 20]. A positive incidence of an abnormal rate of change in covid-19 cases can be observed after 5 days post announcement of double lockdown.

**Fig. 2. Abnormal change rate of covid-19 patients in Tamil Nadu from 24.04.20 to 14.05.20 (Mean Adjusted Method).**

Table 2
Cumulative abnormal change rate of covid-19 patients in Tamil Nadu (Mean adjusted return method).

| Event period | CAR | t stat for CAR |
|--------------|-----|----------------|
| [0,0]        | 0.160 | 1.233 |
| [0,1]        | –0.090 | –0.694 |
| [0,2]        | –0.294 | –2.263* |
| [0,3]        | –0.651 | –5.020** |
| [0,4]        | 0.506 | 3.899** |
| [0,5]        | 0.195 | 1.506 |
| [0,6]        | 0.573 | 4.420** |
| [0,7]        | 0.664 | 5.121** |
| [0,8]        | 0.632 | 4.873** |
| [0,9]        | 0.614 | 4.731** |
| [1,0]        | 1.425 | 10.985** |
| [1,1]        | 1.219 | 9.396** |
| [1,2]        | 1.567 | 12.077** |
| [1,3]        | 1.149 | 8.558** |
| [1,4]        | 1.013 | 7.812** |
| [1,5]        | 0.720 | 5.550** |
| [1,6]        | 0.822 | 6.336** |
| [1,7]        | 0.845 | 6.512** |
| [1,8]        | 0.572 | 4.699** |
| [1,9]        | 0.113 | 0.870 |
| [2,0]        | –0.180 | –1.387 |

** at 1% Significance.
* at 5% Significance.

Table 3
Cumulative abnormal change rate of covid-19 patients in Tamil Nadu (GARCH Models).

| Event period | GARCH-M (1,1) | GARCH (1,1) | E-GARCH (1,1) |
|--------------|---------------|-------------|---------------|
| CAR | t stat for CAR | CAR | t stat for CAR | CAR | t stat for CAR |
| [0,0] | 0.155 | 0.16 | 0.260 | 0.260** | 0.200 | 0.205 |
| [0,1] | 0.106 | –0.51 | 0.160 | 0.164 | –0.006 | –0.029 |
| [0,2] | –0.114 | –1.52 | 0.091 | 0.114 | –0.164 | –1.026 |
| [0,3] | –0.280 | –2.231 | –0.129 | –0.187 | –0.480 | –0.947 |
| [0,4] | 0.469 | 0.98 | 1.105 | 1.789 | 0.719 | 1.400 |
| [0,5] | 0.151 | 0.36 | 0.930 | 1.650 | 0.451 | 0.90 |
| [0,6] | 0.521 | 2.829** | 1.416 | 2.714** | 0.871 | 1.986 |
| [0,7] | 0.604 | 8.406** | 1.626 | 3.332** | 1.004 | 4.970** |
| [0,8] | 0.564 | 19.447** | 1.719 | 3.735** | 1.014 | 7.526** |
| [0,9] | 0.537 | 17.723** | 1.824 | 4.179** | 1.037 | 3.642** |
| [1,0] | 1.340 | 7.224** | 2.726 | 6.550** | 1.890 | 5.857** |
| [1,1] | 1.126 | 5.193** | 2.652 | 6.654** | 1.726 | 5.443** |
| [1,2] | 1.466 | 12.968** | 3.109 | 8.119** | 2.116 | 5.391** |
| [1,3] | 1.040 | 6.929** | 2.831 | 7.672** | 1.740 | 7.608** |
| [1,4] | 0.897 | 16.812** | 2.824 | 7.922** | 1.647 | 6.942** |
| [1,5] | 0.595 | 20.661** | 2.666 | 7.723** | 1.395 | 12.519** |
| [1,6] | 0.520 | 13.024** | 2.724 | 8.135** | 1.370 | 17.860** |
| [1,7] | 0.452 | 31.072** | 2.790 | 8.575** | 1.352 | 17.01** |
| [1,8] | 0.364 | 32.542** | 2.836 | 8.954** | 1.314 | 30.865** |
| [1,9] | 0.244 | 48.44** | 2.852 | 9.240** | 1.244 | 2.207** |
| [2,0] | 1.746 | 6.811** | 5.811 | 16.839** | 2.796 | 4.264** |

** 1% Significance.
A similar trend is also observed in the abnormal rate of change in covid-19 patients, computed using the E-GARCH (1,1) model (Table 3). The results of the E-GARCH model (1,1) reveals an increasing trend in the abnormal rate of change in covid-19 patients at 1% significance (t stat for CAR > 2.58) in the post-event period, from [0, 7] to [0, 20]. The reason behind the evident spike in the spread of covid-19 after 5–6 days post-announcement maybe because it takes at least 5–6 days for the victim to show signs of symptoms, as the incubation period of the corona virus is around 5–6 days (World Health Organization, 2020).

The empirical results of the T statistic of CAR may vary based on the methodology adopted to calibrate the parameters of the event study. Hence, the current study intends to analyze the influence of events on the spread of novel coronavirus using Mean-adjusted return method and GARCH models, namely GARCH (1,1), M-GARCH(1,1) and E-GARCH (1,1).

As observed in Table 4, t statistic of CAR is significant at 1% for all the plausible window sizes (5 days [-2, 2], 11 days [-5, 5], 15 days [-7, 7] and 21 days [10, 10]) considered in the study. The findings signify that the announcement of double lockdown in Tamil Nadu resulted in an abnormal surge in the spread of the novel coronavirus in Tamil Nadu. The announcement of complete lockdown for 4 days created a buying panic among people for essential commodities and several insensitive consumers set out a go by to the prevailing social distancing norms, which further enhanced the spread of the coronavirus. The findings of the event study clearly confirm the aforementioned facts with statistical evidence.

4. Results of regression analysis (CAR)

To further examine the variables that influence the abnormal rate of increase in covid-19 cases, a cross-sectional study is conducted using SPSS by recruiting a sample of data from the five districts of Tamil Nadu, where double lockdown was imposed. The five districts of Tamil Nadu considered in the study are Chennai, Coimbatore, Madurai, Salem and Tiruppur. To determine the sensitivity of the exogenous variables on the abnormal rate of increase in covid-19 cases, the exogenous variables are regressed one by one and the results are summarized in the following sections.

4.1. Population density as a regressor

From the results (Table 5), it is evident that population density has a significant positive influence on the CAR of covid-19 with p = 0.033 (p < 0.05). The adjusted R-square with 0.824 signifies a strong relationship between the population density and CAR. Thus, it is evident that as population density increases the likelihood of covid-19 cases also increases.

4.2. Human development index (HDI) as a regressor

Table 6 signifies that there is a significant influence of human development index (HDI) on cumulative abnormal rise in covid-19, as p = 0.05. Statistically, there exists a strong association between the HDI and CAR of covid-19, as the adjusted R-square value is 0.992. This indicates that as the human development index (HDI) score increases there is a decline in the covid-19 cases.

4.3. Interim Covid care center (ICCC) as regressor

The Interim Covid Care Centers (ICC) was found to have a significant negative impact on the cumulative abnormal rise in covid-19 (p < 0.05, R-square-0.833). This indicates that an increase in the Interim Covid Care Centers (ICCC) results in a decrease in covid-19 cases, as covid-19 patients are treated in isolation in these centers (Table 7).

4.4. Multiple linear regression analysis of CAR

Further, the combined effects of the exogenous variables on the CAR of covid-19 are determined using multiple linear regression analysis.

The study conducted multiple linear regression to ascertain the strength of association between the predictors and CAR of covid-19. The model was proved to be robust as R-square = 0.887 and adjusted R-square = 0.749 with p < 0.05. Hence, ICC, HDI and population density are strongly associated with the cumulative abnormal rise in covid-19 cases. From the results, the following regression equation is estimated, \[ \text{CAR of covid-19} = 31587.531 – 1076.099 \times (\text{ICCC}) + 0.117 \times (\text{Population Density}) -24206.001 \times (\text{HDI}) + \epsilon \]

4.5. Endogeneity test of regressors

Endogenous regressors are often encountered in econometric models, and failure to correct for endogeneity could give inappropriate results. For this purpose, the study employs the two-stage least squares (2SLS) method to test the endogeneity of the regressors.

4.5.1. Endogeneity test of population density

H1. Population Density is an exogenous regressor.

From the results of the 2 SLS regression (Table 9), it is evident that the regressor “Population Density” is exogenous, as p > 0.05 (see Table 8). Hence the hypothesis, H1 is accepted, which implies “Population Density” is an exogenous variable (see Table 10).

4.5.2. Endogeneity test for Interim Covid Care Centers (ICCC)

To test the endogeneity of the predictor “Interim Covid Care Centers”, a variable “Test per Million (TPR)” which records the number of covid test undertaken is chosen as an instrumental variable. 2SLS, a statistical test is undertaken to test the following hypothesis.

H2. Interim Covid Care Centers (ICCC) is an exogenous regressor.

The results of the analysis are exhibited in the table. It is statistically evident that the regressor “Interim Covid Care Centers (ICCC)” is exogenous, as p > 0.05, thus accepting the hypothesis H2.

4.5.3. Endogeneity test for human development index (HDI)

The suspected endogenous regressor ‘Human Development Index (HDI)’ is tested for its endogeneity using two-stage least squares regression in SPSS with ‘Literacy Rate’ as an instrumental variable. The following hypothesis was proposed.

H3. Human Development Index (HDI) is an exogenous regressor.

From the results of the two-stage least squares regression, H3 hypothesis is accepted as the t-statistic value is 0.710 (p > 0.05). Thus, it is concluded that the regressor “Human Development Index (HDI)” is an exogenous variable.

Table 4

| Event window | GARCH (1,1) CAR | t-statistics | EGARCH (1,1) CAR | t-statistics | GARCH-M (1,1) CAR | t-statistics |
|--------------|----------------|--------------|-----------------|--------------|-----------------|--------------|
| (-5, 5)      | 1.841          | 7.179**      | 1.201           | 6.528**      | 5.167           | 2.909**      |
| (-2, 2)      | -0.094         | -5.936**     | -0.35           | -1.10        | -2.150          | -2.949**     |
| (-10, 10)    | 3.596          | 16.474**     | 2.316           | 27.327**     | 1.266           | 9.618**      |
| (7, 7)       | 3.509          | 21.009**     | 2.613           | 18.073**     | 18.980          | 28.125**     |

** 1% Significance.
5. Conclusion and implications

The policymakers of several countries attributed the spike in covid-19 cases to their enhanced testing capability. The aforementioned contention is deliberately profused in peoples’ minds in order to negate the fact of the covid-19 community spread in their country. This spurious belief is falsified for our sample of data, by determining covid-19 cases for every 1000 tests done in Tamil Nadu from March to June 2020. The steady increase in covid-19 cases for every 1000 tests done in Tamil Nadu from March to June 2020, exhibited in Table 11, deciphers that the increase in covid-19 cases in Tamil Nadu is real and not simply driven by the increased testing regime (see Table 12).

In summary, the research paper progressively exemplified the incidence of cobra effect on the spread of novel coronavirus caused due to the double lockdown strategy implemented in Tamil Nadu. For this purpose, the study derived panel data of new covid-19 cases reported daily and conducted a longitudinal analysis. The findings of the event study methodology statistically proved that the Tamil Nadu’s double lockdown strategy which aimed at flattening the spread of novel coronavirus curve, actually amplified it. This counter effect is termed as the “cobra effect” in the literature of economics.

The main reason behind this counter-effect is panic buying. Panic buying eventuates among people when there is a fear of price rise or shortage of essential products (e.g. food supply, medicines, etc.). Consequently, people become anxious and tend to stockpile indispensable items [26]. Panic buying among people resulted in long queues and clustered markets, where covid-19 norms like social distancing were imprudently ignored. Unlike hurricanes and snowstorms, where panic buying is also discernible, this phenomenon has an unprecedented impact on the spread of covid-19 as social distancing norms were
Though the cobra effect is applied in the field of medicine [27] and finance [4], to the best of our knowledge, no studies have tested the incidence of cobra effect on the containment strategy of a pandemic disease like covid-19. Testing the unprecedented consequences (cobra effect) of double lockdown strategy on the growth rate of covid-19 cases is of supreme importance since a wrong move by the policymakers will further intensify the spread of the pandemic. Furthermore, the economically costly lockdown will have a catastrophic effect on the economy, affecting both lives and livelihood of the people. The current study does not mean to suggest that the double lockdown strategy is a wrong move by the government, instead intends to contribute to policymaking that would assist in making appropriate decisions at the time of crisis like covid-19. To mitigate the empirically confirmed unprecedented consequences of double lockdown strategy in containing the pandemic, policymakers should take precautionary measures like announcing the complete lockdown well ahead of the implementation day. This countermeasure aids people to plan their purchases and travel with appropriate social distancing measures. By doing so, the unforeseen consequences like creating crowded markets can be substantially minimized.

There are few other factors like people’s reckless attitude in meeting covid-19 safety measures (E.g. wearing masks properly, washing hands frequently, etc.), delay in closure of Koyambedu market, one of largest wholesale markets for perishables located in Tamil Nadu, India, etc. Though the aforementioned factors contribute to the spread of novel coronavirus, intensively it is “Panic Buying” that resulted in the rapid spread of covid-19.

From the findings of the study, it is apparently evident that one-size-fits all lockdown policy is a blunt strategy to curb the spread of novel coronavirus. Hence, government policymakers should contemplate for alternative strategies to reduce the transmission of the covid-19 virus in a relatively similar magnitude, but one that is more conducive to the starved economy. Unlike the complete lockdown which entails economic loss to the country, a foot traffic restriction policy based on real-time risk estimators is a much softer but wiser strategy to curb the spread of the covid-19 pandemic [28].

It is highly recommended to implement a web-based system like COSRE (community social risk estimator) to determine the probability of acquiring covid-19 in the community [28]. This enables the policymakers to allow human traffics in low-risk areas (less than 25%) and restrict human movements in hot spot areas with a risk of more than 50% probability. Lockdowns only in these hotspots would dampen the spread of covid-19 without reflecting much on the economic disasters as imposed by full lock-down.

### Table 10
Results of endogeneity test of ICCC.

| Table 10 Results of endogeneity test of ICCC. |
| --- |
| **Regression statistics** |
| R Square | 0.196 |
| Adjusted R square | -0.072 |
| Std. Error | 4703.454 |
| Significance | 0.455 |
| F | 0.732 |

| ANOVA |
| --- |
| Model | Sum of squares | Df | Mean square |
| Regression | 126900042.3 | 1 | 126900042.3 |
| Residual | 520364044 | 3 | 173454681.3 |
| Total | 647264086.3 | 4 | |

| Unstandardized coefficient | Standardized coefficient beta | T | p |
| --- | --- | --- | --- |
| Constant | -18648.595 | 6210.344 | -0.842 | 0.462 |
| Population density | 1299.709 | 332.004 | 1.049 | 0.855 |

### Table 11
Results of endogeneity test of HDI.

| Table 11 Results of endogeneity test of HDI. |
| --- |
| **Regression statistics** |
| R Square | 0.075 |
| Adjusted R square | -0.075 |
| Std. error | 9092.076 |
| Significance | 0.656 |
| F | 0.242 |

| ANOVA |
| --- |
| Model | Sum of squares | Df | Mean Square |
| Regression | 20020536.068 | 1 | 20020536.068 |
| Residual | 248030245.901 | 3 | 82676748.634 |
| Total | 268050781.969 | 4 | |

| Unstandardized coefficient | Standardized coefficient beta | T | p |
| --- | --- | --- | --- |
| Constant | -21226.901 | 51884.041 | -0.409 | 0.710 |
| HDI | 34620.753 | 70354.253 | 0.378 | 0.492 |

### Table 12
The spike in testing is not driving the spike in covid-19 positive cases.

| Table 12 The spike in testing is not driving the spike in covid-19 positive cases. |
| --- |
| **Time frame** | Tested samples | Positive cases | Positive cases per 1000 tests |
| Till 7.3.20 | 63 | 1 | 16 |
| 8.3.20 to 17.3.20 | 77 | 0 | 0 |
| 18.3.20 to 27.3.20 | 1203 | 37 | 31 |
| 28.3.20 to 8.4.20 | 14062 | 453 | 32 |
| 9.4.20 to 18.4.20 | 21368 | 733 | 34 |
| 19.4.20 to 28.4.20 | 33108 | 1173 | 35 |
| 29.4.20 to 8.5.20 | 111635 | 4072 | 36 |
| 9.5.20 to 18.5.20 | 121425 | 5751 | 47 |
| 18.5.20 to 28.5.20 | 117375 | 7612 | 65 |
| 29.5.20 to 7.6.20 | 137754 | 12295 | 89 |

| Declaration of competing interest |
| --- |
| No potential competing interest was reported by the authors. |

### References

1. F.E. Alvarez, D. Argente, F. Lippi, A Simple Planning Problem for Covid-19 Lockdown (No. W26981), National Bureau of Economic Research, 2020.
2. M. Bin, P. Cheung, E. Crisostomi, P. Ferraro, C. Myant, T. Parisini, R. Shorten, On Fast Multi-Shot Epidemic Interventions for Post Lock-Down Mitigation: Implications for Simple Covid-19 Models, 2020 arXiv preprint, 2003.09930.
3. V. Sajeev Kumar, Double Lockdown Idukki Pepper Arrivals to Kochi, 2020. https://www.thehindubusinessline.com/markets/commodities/double-lockdown-in-dukki-ikkayam-hit-pepper-arrivals-to-kochi/article3146619.ece.
4. R. Bajo-Buenestado, M.A. Borrella-Mas, Passing-through taxes beyond borders with a cohes effect, J. Publ. Econ. 177 (2019) 104040.
5. P. Warczak, The Cobra Effect: Kisor, Roberts, and the Law of Unintended Consequences, 2020 (Akron Law Review, Forthcoming).
6. P.K. Ozili, T. Arun, Spillover of COVID-19: Impact on the Global Economy, 2020. Available at: SSRN 3502570.
7. D. Ray, S. Subramanian, L. Vandewalle, India’s Lockdown (No. BOOK), Centre for Economic Policy Research, 2020.
8. V. Patel, Empowering global mental health in the time of Covid 19, Asian Journal of Psychiatry 51 (2020) 102460.
M.A. Rahman, N. Zaman, A.T. Asyhari, F. Al-Turjman, M.Z.A. Bhuiyan, M.F. Zolkipli, Data-driven dynamic clustering framework for mitigating the adverse economic impact of Covid-19 lockdown practices, Sustainable Cities and Society 62 (2020) 102372.

A. Suppasri, M. Kitamura, H. Tsukuda, S.P. Boret, G. Pescaroli, Y. Onoda, N. Leelawat, Perceptions of the COVID-19 pandemic in Japan with respect to cultural, information, disaster and social issues, Progress in Disaster Science (2021) 100158.

Q. Xu, V. Chang, C.H. Hsu, Event study and principal component analysis based on sentiment analysis—a combined methodology to study the stock market with an empirical study, Inf. Syst. Front 22 (3) (2020) 1021–1037.

P. Theerthaana, A.K. Manzoor, Is Bitcoin Gaining Cash during Cashless Times in India? an Event Study Approach, 2018.

Q. Wang, E.W. Ngai, Event Study Methodology in Business Research: a Bibliometric Analysis, Industrial Management & Data Systems, 2020.

A. McWilliams, D. Siegel, Event studies in management research: theoretical and empirical issues, Acad. Manag. J. 40 (3) (1997) 626–657.

J. Binder, The event study methodology since 1969, Rev. Quant. Finance Account. 11 (2) (1998) 111–137.

W. Oh, M.J. Gallivan, J.W. Kim, The market’s perception of the transactional risks of information technology outsourcing announcements, J. Manag. Inf. Syst. 22 (4) (2006) 271–303.

F. Nagm, K. Kautz, The market value impact of IT investment announcements—An event study, J. Inf. Technol. Theor. Appl. 9 (3) (2009) 5.

D. Chatterjee, C. Pacini, V. Sambamurthy, The shareholder-wealth and trading-volume effects of information-technology infrastructure investments, J. Manag. Inf. Syst. 19 (2) (2002) 7–42.

C. Ferguson, F. Finn, J. Hall, Electronic commerce investments, the resource-based view of the firm, and firm market value, Int. J. Account. Inf. Syst. 6 (1) (2005) 5–29.

J. Holler, Event-study Methodology and Statistical Significance. Event-Study Methodology and Statistical Significance, 2014, pp. 5–10.

S.J. Brown, J.B. Warner, Using daily stock returns: the case of event studies, J. Financ. Econ. 14 (1) (1985) 3–31.

T. Bollerslev, Generalized autoregressive conditional heteroskedasticity, J. Econom. 31 (3) (1986) 307–327.

S. Ling, M. McAleer, Asymptotic theory for a vector ARMA-GARCH model, Econom. Theor. (2003) 280–310.

J. Yoon, R. Narasimhan, M.K. Kim, Retailer’s sourcing strategy under consumer stockpiling in anticipation of supply disruptions, Int. J. Prod. Res. 56 (10) (2018) 3615–3635.

M. Attarba, J. Bigelow, M.M. Merzenich, Unintended consequences of white noise therapy for tinnitus—otolaryngology’s cobra effect: a review, JAMA Otolaryngology–Head & Neck Surgery 144 (10) (2018) 938–943.

Z. Sun, L. Di, W. Sprigg, D. Tong, M. Casal, Community venue exposure risk estimator for the COVID-19 pandemic, Health Place 66 (2020) 102450.

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