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A Blended Approach to Analyze Indian Stock Market during COVID-19

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Abstract: The coronavirus (COVID-19) outbreak has proven to be one of the most defining health and socio-economic crisis of this century. The effect of the coronavirus pandemic on the Indian economy has been particularly disturbing. This work blends statistical and semantic approaches to analyze the effect of the COVID-19 pandemic on the Indian stock market. It empirically investigates the impact of the significant events such as lockdown, unlock, and vaccination announcements on eight key NIFTY-50 sectors of the Indian stock market, using event-based statistical analysis. The micro blogging platform Twitter is deployed to extract COVID-19 related tweets, pertaining to the Indian stock market, and perform sentiment analysis to analyze and understand the general sentiment of consumers towards the stock market. Results and detailed Inferences are drawn from these two completely different facets viz. the objective results drawn from the stock market and the subjective perspectives drawn from the social media in order to holistically analyze the impact of the COVID 19 pandemic on the Indian stock market.

Keywords: COVID-19, NIFTY-50, Stock Market, Event-based Study, Sentimental Analysis.

1. Introduction

The coronavirus (COVID-19) outbreak came to light on December 31, 2019, when China informed the World Health Organization (WHO) about a cluster case of pneumonia from an unknown cause in Wuhan City in Hubei province. On January 9, 2020, the WHO issued a statement saying Chinese researchers have made a preliminary determination of the virus as “novel coronavirus”, which has since led to define the most significant global health crisis of our times. What is more noteworthy is that this pandemic has also proven to be the cause of an unprecedented socio-economic crisis.

The effect of the coronavirus pandemic on the Indian economy has been very unsettling. The economy nosedived to an all-time low after the Independence of the country in 1947. Falling domestic demand and exports, lockdown leading to the closing of business units, disruption of supply chain and global trade and increasing unemployment rate are only some of the factors that have led to an adverse effect on almost all stock market sectors. Huge loss of life and uncertainty fueled anxiety and depression and served to further deteriorate investor sentiment.

In this paper, we undertake to study the impact of the COVID-19 pandemic on eight key sectors of the NIFTY 50 index, namely, Pharma, Oil & Gas, IT, Consumer Goods, Real Estate, Automobiles, Metals, and Banks. We choose four significant events in a period of little over one year (Nov 2019 – March 2021). Using the Market Model [1], we assess the impact of lockdown, first partial unlock, full unlock, and the vaccination announcements on the aforementioned eight sectors of the Indian stock market.

It is a widely accepted fact that investor sentiment is a significant determiner of the behavior of stock markets worldwide. We, therefore, complement the event-based statistical study by sentiment analysis of the people’s perceptions, in the time of the pandemic, towards the eight sectors chosen for study. Detailed inferences are drawn in Sections 4D and 5B of the paper to show that a sentimental study (section 5) complements and completes the results drawn from the statistical study (Section 4).

The paper is organized as follows: Section 2 reviews the related work and contrasts our work from the earlier solitary works in two directions viz. event based studies and the sentiment-based studies. Section 3 introduces a proposed twin impact model for assessing the impact of COVID – 19 on the Indian stock market. Section 4 details

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the empirical event-based study, its results, and inferences. Section 5 presents the sentimental analysis, its results, and inferences. Section 6 summarizes the work and discusses some directions for future work.

2. Related Work

The discussion of the literature related to our work is presented in this section. We also outline research gaps in the earlier works, and try to cover some of these gaps in this paper. The discussion is organized as follows: previous works related to event-based studies of the stock market are discussed first, followed by a review of some works on the sentimental analysis of stocks.

The impact of COVID-19 on the stock market by analyzing the data of daily closing prices of stock indices, NIFTY and SENSEX, from September 3, 2019, to July 10, 2020, is studied in [2]. The paper concluded that the return on stocks was higher in the pre-COVID-19 days as compared to the COVID-19 days. However, the study does not bring about a sector-wise analysis. This is in contrast to our work, which divides the COVID-19 scenario into different phases and gauges the effect of lockdown, unlock, and vaccination period on eight sectors of Indian economy. A study on the effects of the pandemic on the stocks of various oil companies of Asia is presented in [3]. Using the event study approach, an empirical study on the performance and effect of the COVID-19 pandemic on the selected Chinese industries has been undertaken in [4]. The effect of the COVID-19 pandemic on the Egyptian stock market using event studies has been presented in [5] and that on the Istanbul stock market has been presented in [6]. A study of the effect of the COVID-19 pandemic on US stock markets is presented in [7]. A comparative analysis of the stock price prediction using the algorithms long short-term memory (LSTM) and auto-regressive integrated moving average exogenous (ARIMAX) has been taken up in [8]. The work also contrasted the efficacy of both the algorithms without and with sentiment analysis. It was established that sentiment analysis adds to the value of results in both cases. In contrast to the above works, the work presented in this paper not only studies the effect on the Indian stock market around four important events using event-based studies, over a period of a year, but also studies the perception of consumers and investors by analyzing their sentiments towards various stocks during the pandemic. As can be seen from inferences, this enriches and completes the statistical study.

Works in the area of sentiment analysis of the effect of COVID-19 pandemic on the stock market are discussed next. Some primitive works in this area include a sentiment-based study on the stock Market using Twitter [9]. However, the research in this paper is not specific to the pandemic. The response of the stock market to the COVID-19 lockdown announcement is studied in [1]. 31 Bombay stock exchange companies are studied to conclude that the responses of people were more negative during the pre-lockdown period than the lockdown period.

Tushar [10] reports a high correlation between stock markets prices and the Twitter sentiments by using the Granger's Casualty Analysis. An Expert Model Mining System (EMMS) is used in the paper for validating the forecasted returns. The study concludes that the discussion topics on Twitter prove to be a major deriver for the short-term changes in stock prices and stock market indices. A model using Python language programming and TextBlob to predict the investor reaction to COVID-19 news has been proposed in [11]. The paper also discusses existing work related to sentiment analysis and NLP techniques used by researchers to design forecasting models based on extracted data from social media sites like Twitter. These papers set the motivation for inclusion of a sentimental study in our paper.

Stock market prediction in terms of forecasting the probability of possible data latency arrival from the different sources has been taken up in [12]. The work takes into account the parameters, such as USD, OIL Price, and Gold Price with an equal arrival rate and shows improved results when considering the affecting parameters. The effect of the different types of windowing to process the continuously arriving data has been studied in [13]. The paper analyses the watermark and trigger approach to manage the unconventional processing of unbounded data such as a click stream data.

Some studies involving sentiment-based study for prediction and forecasting in the stock markets are discussed next. A sentiment analyzer that clusters the tweets based on their sentiments and uses it for price movement prediction via machine learning models is presented in [14]. A study on the perception of people regarding the stock markets during the time of the COVID pandemic for the prediction of stock prices has also been undertaken in [15]. The paper makes use of six machine learning algorithms, namely, Decision Tree method, Random Forest method, Logistic Regression method, Naïve Bayes method, Support Vector Machine method, and the KNN method. In contrast to these works, we feel that a stock market's volatility depends upon various socio, political, economic aspects that may not all be modeled with the help of sentimental analytics alone. So, we focus on descriptive sentimental analysis of stock market in the current work.

3. Sentimental Event-Based Modeling of Indian Stock Market

In this section, we propose a twin impact model to study the Indian stock market. The data and preprocessing details are outlined next, followed by the programming environment underlying the implementation.

A. The Twin Impact Model

We propose a twin impact model that builds upon two completely different facets viz. the objective indices drawn from the stock market and the subjective perspectives drawn from the social media and combines them to draw inferences about the impact of the COVID-19 pandemic on the Indian stock market. The model is based upon the rationale that a mere objective or subjective study is not enough to characterize any effect on the stock market. Stock markets are very volatile and depend upon a large number of political and economic factors, which also vary the investor sentiments. Therefore, though the data from the major stock exchanges provide insight into the reaction of the stock market to the pandemic, studying public perceptions of stocks complements and holistically completes the analysis. In the objective analysis, we not only study the variations in the stock market over different granularities of time using event-based statistical study, which has been shown to be a versatile, time-tested technique to study the reaction of stock markets worldwide to various events and catastrophes. For subjective analysis, stock market tweets during the time of the pandemic have been sentimentally analyzed.

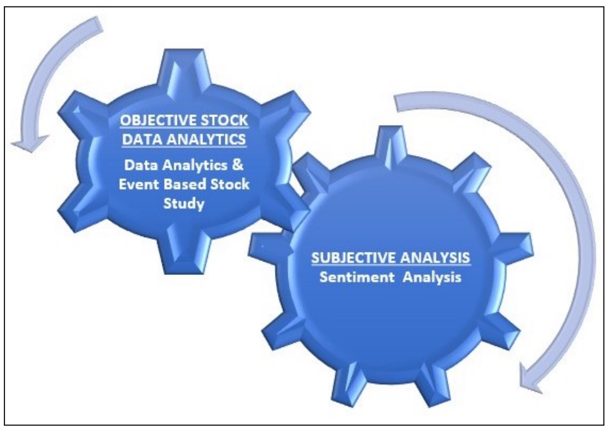

Figure 1. Core components of the twin impact model for the study of Indian Stock Market

The two components of the proposed model are shown in Figure 1. The first component works towards the realization of the objective facet of stock data analysis, wherein the data drawn from the stock market is subjected to statistical data analysis based on the event model. The second component focuses on the subjective facet of data analysis wherein the sentiments of data related to the stock market during the pandemic time are analyzed. The results of the event-based study and sentiment analysis can be corroborated to draw consolidated inferences about the stock market during the COVID-19 pandemic.

A detailed schematic representation of the proposed impact model is presented in Figure 2. The objective stock data analytics component consists of a stock data collector module that draws out data from the NIFTY 50 index [16]. The stock data selector module filters the stock data both horizontally and vertically, based on the companies selected for study in each sector and the desired time (event) windows. The time (event) windows are introduced in Section 4A. Since the data from the NIFTY index is generally both complete and clean, the data preprocessing for stock data is minimal. For statistical analysis, the filtered data from the stock data selector module is subjected to the event-based study that empirically investigates the sector-wise effect of the pandemic on the stock market. In the process, several aggregates are computed, standard statistical metrics are derived and the results are visualized using Graphs.

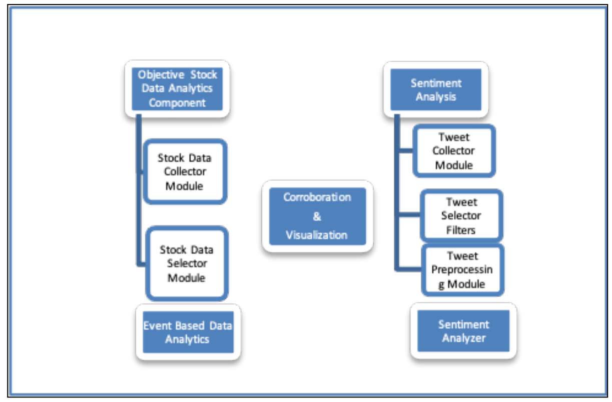

Figure 2. Schematic Representation of the twin impact model.

The Sentiment Analysis Component consists of a module that scrapes tweets from social media which are then subjected to various filters comprising of selected companies for each sector to be studied. Subjective filters, carefully designed to filter tweets that contain opinions related to the pandemic and stock market companies, within the sectors chosen for study, are also applied. The tweet preprocessing module cleans the tweets, putting them into a format required for further study. Finally, the sentiment analyzer examines and assigns the polarity of sentiment expressed in the tweets. Inferences from event-based statistical data analytics and sentiment analysis over different event windows and pandemic time windows are drawn in order to aid manual corroboration of time-variant patterns and subjective inferences.

B. Data and Implementation Details

The dataset for the event-based data analytics study was taken from the official website of the National Stock Exchange India [16]. The data was collected in the CSV file format. Using Python 3.8 as the programming environment, Pandas was used for data cleaning and analysis. NumPy was used to work with multidimensional arrays. matplotlib was used for the representation of the graphs of different types and the DateTime library was used for the data and time management. For sentimental analysis, the tweets were scraped from the Twitter handles of the top ten companies from NIFTY 50, for each of the eight different sectors of the stock market chosen for study. The data for the sentimental study was scraped from different Twitter handles using Tweepy, an open-source python package. A total of 6.5k tweets were extracted from each sector for study in the period Nov 2019 - Feb 2021. The extracted tweets were then filtered using keywords related to stocks, sector names, and COVID pandemic synonyms. After the data selection, tweets were preprocessed to treat the missing values, replacement of special characters, and replacement of all the uppercase to lowercase, etc. TextBlob, an open-source python library for processing textual data, was used for computing the sentiment polarity of the filtered tweets. The library was used in our work to extract the noun phrases and for computing sentiment objectivity and polarity of the extracted tweets. The modules OS and time were used to interface with the operating system and segregate the data into different time spans respectively.

4. Event-Based Empirical Study

Event-based studies are statistical studies that have been effectively used since [17] in various fields such as stock market, accounting and finance, marketing, economics, IT and political science, etc. to study the effect of an event on the stock prices[1, 4, 18, 19]. This is done by studying the abnormal returns of the stock prices after the occurrence of the event being examined, as compared to the normal returns in some period preceding the event and after the event.

In this paper, we exploit the event-based statistical methodology to examine the response of the Indian stock market to the COVID-19 pandemic. To accomplish this, the important events and event windows were identified. These are detailed in Section 4A. Section 4B details the concepts of Abnormal Returns (AR), Cumulative Abnormal Returns (CAR), and t-tests, their computations, and how they were deployed for the event study of stocks. Section 4C details the results and Section 4D presents the detailed inferences derived from the event-based study.

A. *Events and Event Windows*

Four events were chosen for the study from a span of a little over one year, starting from 11th February 2020 and extending up to 2nd March 2021. The chosen events were the announcement of the first lockdown on 25th March 2020, the announcement of the first partial unlock on 1st June 2020 when only some select services and offices were allowed to operate, last unlock announcement on 1st November 2020 when most of the market, school, colleges were allowed to open and the first day of vaccination, on 18th January 2021.

Event Window: An event window denotes the period (in trading days) just after and before the happening of an event being examined. A time of 20 trading days (t-10, t+10) was chosen in this paper for the event window. The notation t (0,0) denotes the event day so the event window extends from ten days before and up to ten days after the event.

Estimation Window: An estimation window is a time (in trading days), chosen to study the normal returns of the stocks prior to the happening of the event being analyzed. In this paper, we choose an estimation period of 20 trading days (t-30, t-10). The estimation window precedes the event window.

Post Event Window: A post-event window is a time (in trading days), chosen to study the normal returns of the stocks after the happening of the event being analyzed. In this paper, we choose the post-event window to be of 20 trading days (t+10, t+30), starting just after the event window i.e., after the first ten days of the happening of the event and extending up to 30 trading days after the event. Figure 3 summarizes the four events and the corresponding windows with actual dates used in this paper for the event study.

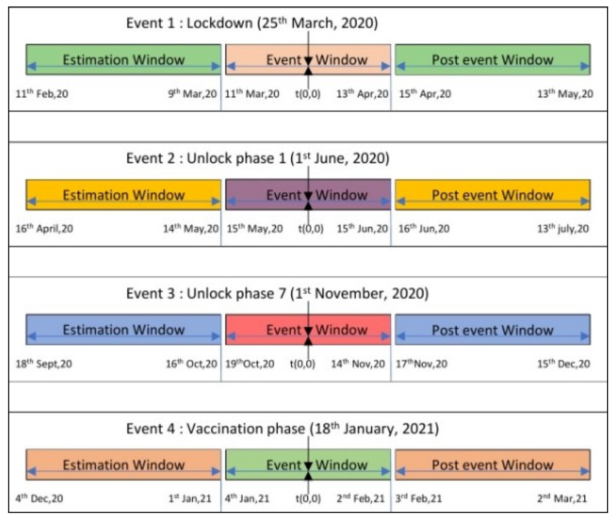

Figure 3. Estimation window, Event window, and Post Event windows for the four events undertaken for the study.

B. *Stock Market Returns and t-test*

The concepts of Abnormal Returns (AR), Cumulative Abnormal Returns (CAR), and t-tests have been used for a very long time, traditionally, to examine the impact of an event on stock prices. An abnormal return signifies a deviation from the stock's normal i.e., expected return. The abnormal returns can be either positive or negative but their quantum serves as an indicator of the risk in a stock's price. However, the returns of a stock could be abnormal for a day or two by chance, due to some external or unforeseen events. So, it is customary to sum abnormal returns over a period of time. This summation is called the cumulative abnormal return (CAR) and is used to measure the impact of events have on stock prices. The quantum of change in the CAR value implies the proportionate effect of the event being studied on the stock prices. We employ the market model [1] for event study in this paper. The normal return, also known as the expected return, for a stock, is computed as follows:

Normal Return = α + (β * Market Return) (1)

where α and β denote intercept and slope respectively and are computed using the excel form *lao* slope and intercept in excel provided with the x, y co-ordinate ranges. The x co-ordinate range denotes the stock return of the estimation window and the y co-ordinate range denotes the market return of the estimation window. The abnormal return at a time instant t, AR_t, as per the market model, is computed as follows:

$$(AR_t) = ActualReturn(R_{i,t}) - NormalReturn(ER_{i,t})(2)$$

$R_{i,t}$, denotes the actual return rate of stock i at time t and is computed as:

$$R_{i,t} = (CP_{i,t} - CP_{i,t-1})/CP_{i,t-1}(3)$$

where $CP_{i,t}$ denotes the price a stock i closes at a particular time instant t. $ER_{j,t}$ denotes the return rate of stock j that is expected at time t and is computed as:

$\mathrm{ER}_{j,t} = Intercept(x1 : x2, y1 : y2) + Slope(x1 : x2, y1 : y2) * E_{m,t}(4)$

where $E_{m,t}$ signifies the market return rate at time t. It is computed as:

$$E_{m,t} = (RM_{i,t} - RM_{i,t-1})/RM_{i,t-1}(5)$$

$RM_{i,t}$ denotes the market return of stock i at time t.

The cumulative abnormal return at a time instant t, as per the market model, is computed as follows: Cumulative Abnormal Return $(CAR_t) = {}^{n}_{(i=1)}AR_i$, where n is the number of trading days in the window being considered. CAR is also sometimes expressed as:

$$CAR_t = CAR_{t-1} + AR_t, (6)$$

The t-test is a statistical inference tool to determine if there exists a significant difference between two related samples. We use a two-tailed t-test to ascertain the difference between the average CAR values of the estimation period versus the period just before and after the event. Usually, the following hypothesis are assumed for the events being studied:

Null Hypothesis (H0): The announcement of lockdown has not affected the stock market.

Alternate Hypothesis (H1): The announcement of lockdown has affected the market. Using the two-tailed t-test, a t-value is computed, which tells the deviation of the average CAR value of event day from the estimation period. The computation of the t-value is done as follows:

t - value = AR / Std. Error (x1:x2, y1:y2) (7)

If this value is more than 1.96 i.e., 5% of probability (as read from the standard t-table values according to the alpha value), it implies that the event has had a significant positive impact on the stock market and hence the null hypothesis can be rejected and alternate Hypothesis accepted. If the t-value is less than 1.96, the impact on the stock market sector being studied is adjudged as negative. This is because in this case hypothesis H0 is rejected, implying that hypothesis H1is accepted.

C. Results

The graphs of CAR computations for the eight sectors of the stock market undertaken for the study are shown in Figure 4.

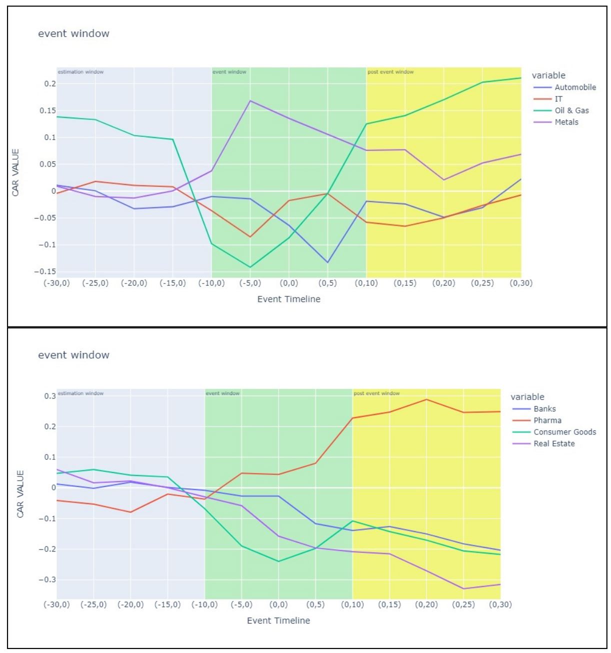

Figure 4. CAR (Cumulative Abnormal Return) value for the eight sectors during the first event

It can be observed from Figure 4, that almost all the sectors showed steady CAR values with very little variations during the estimation window. It is interesting to note however that Oil Gas sector shows a very sharp decline almost fifteen days before the announcement of lockdown. The event window witnesses small variations in the IT sector. The Automobile, Oil & Gas show a significant decline in CAR values. The Banking sector also shows a decline. Consumer and Goods shows a marked decline in the CAR value while the Real Estate sector also shows a decline. Pharma and Metals Sectors show a marked incline in the CAR values. In the post-event window, the Automobile sector shows a little, almost negligible, bounce back in the CAR value. IT and Metal sectors also show very few variations in the CAR values. Consumer Goods and Bank and the Real Estate sector sectors show a decline. Pharma and Oil & Gas continue to show an incline in the CAR values. As noted earlier, while the quantum of variation in the CAR value indicates the amount of effect of the event on the stock prices, a t-test can point out the same with certainty. Hence, we perform a two-tailed t-test. The graphs of the computed t-values for the eight sectors are shown in Figure 5.

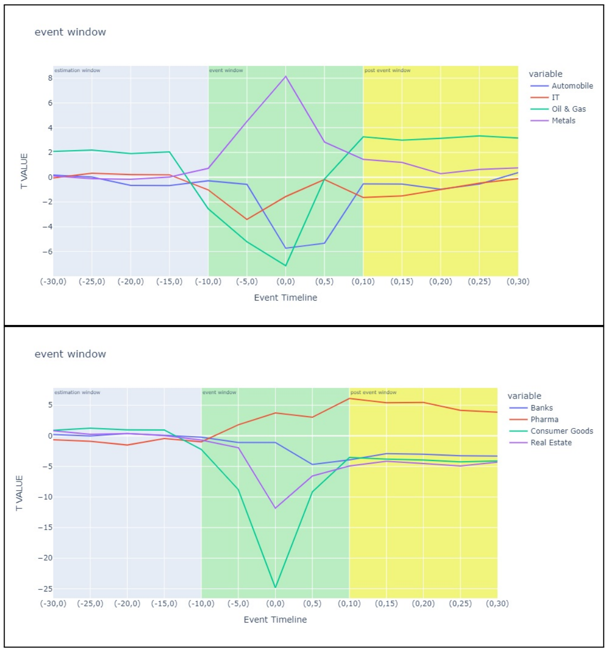

Figure 5. Graphs showing the t-value for the eight sectors for the first event

Based on the computed CAR values and t-values, the acceptance or rejection of the null hypothesis is shown in Tables I and II.

For event two, i.e., the first partial unlock, assuming the same null hypothesis (H0) and alternate hypothesis (H1) as event 1, the Graphs of CAR values are shown in Figure 6.

The graphs of the computed t-values for the eight sectors are shown in Figure 7. Based on the computed CAR values and t-values, the acceptance or rejection of the null hypothesis is shown in Tables III and IV. The detailed inferences are presented in Section 4D.

For event three i.e., the last unlock phase, we assume our null hypothesis H0 and alternate hypothesis H1, the same as for the earlier two events, as follows:

Null Hypothesis (H0): The announcement of the last unlock has not affected the stock market. Alternate Hypothesis (H1): The announcement of the last unlock has affected the market. Figures 8 and 9 show the Graphs of the computed CAR values and t-values of the eight sectors for the third event respectively. Based on the computed CAR values and t-values, the acceptance or rejection of the null hypothesis is shown in Tables V and VI. The detailed inferences, based on these results are presented in Section

Figure 6. Graphs showing the CAR values of the eight sectors for the second event

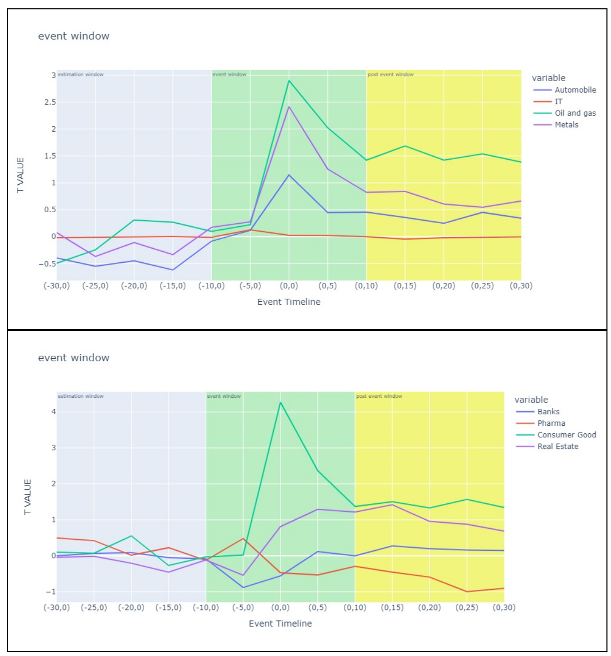

Figure 7. Graphs showing the t-value of the eight sectors for the second event

4D.

For event four i.e., the vaccination phase, we assume our null hypothesis H0 and alternate hypothesis H1 to be the same as the earlier three events, stated as follows: Null Hypothesis (H0): The vaccination phase has not affected the

TABLE I. Results of The Hypothesis Testing For Automobile, IT, Oil & Gas And Metals Sectors For The First Event

Event Timeline	Automobile			IT			Oil & Gas			Metals		
	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis
(-30,0)	0.01092297	0.17936762	Accepted	-0.0039191	-0.0639748	Accepted	0.138245394	2.078526	Rejected	0.00939787	0.10303547	Accepted
(-25,0)	0.00069178	0.01244408	Accepted	0.01810575	0.32376815	Accepted	0.133021013	2.190865	Rejected	-0.0098815	-0.1186776	Accepted
(-20,0)	-0.0327233	-0.6581211	Accepted	0.01079628	0.21584734	Accepted	0.103631886	1.908288	Accepted	-0.0129041	-0.1732724	Accepted
(-15,0)	-0.0288887	-0.6708833	Accepted	0.0082969	0.19153881	Accepted	0.096304538	2.047701	Rejected	0.00061594	0.00955009	Accepted
(-10,0)	-0.0100662	-0.2863053	Accepted	-0.0361173	-1.0211814	Accepted	-0.09762018	-2.54217	Rejected	0.03773186	0.7165166	Accepted
(-5,0)	-0.0141528	-0.5692729	Accepted	-0.0851148	-3.4033588	Rejected	-0.141498177	-5.21112	Rejected	0.16793079	4.50986309	Rejected
(0,0)	-0.0636743	-5.7270174	Rejected	-0.0174495	-1.5601608	Accepted	-0.086780786	-7.14643	Rejected	0.13550091	8.13692353	Rejected
(0,5)	-0.1325733	-5.3325543	Rejected	-0.0046282	-0.1850608	Accepted	-0.004075546	-0.15009	Accepted	0.1057849	2.84090477	Rejected
(0,10)	-0.0187351	-0.5328689	Accepted	-0.0579073	-1.6372735	Accepted	0.125180044	3.259872	Rejected	0.07594185	1.44211258	Accepted
(0,15)	-0.0239457	-0.5560901	Accepted	-0.0653635	-1.508958	Accepted	0.140581072	2.989143	Rejected	0.07694997	1.19311101	Accepted
(0,20)	-0.0483635	-0.9726729	Accepted	-0.0496568	-0.9927767	Accepted	0.170244857	3.134905	Rejected	0.02102125	0.28226799	Accepted
(0,25)	-0.0306985	-0.5522185	Accepted	-0.0263912	-0.4719283	Accepted	0.202749097	3.339292	Rejected	0.05232998	0.62849034	Accepted
(0,30)	0.02262612	0.37154686	Accepted	-0.0070286	-0.1147342	Accepted	0.210576159	3.166022	Rejected	0.06857951	0.75188562	Accepted

stock market. Alternate Hypothesis (H1): The Vaccination phase has affected the market. Figures 10 and 11 show the Graphs of the computed CAR values and t-values of the eight sectors for the fourth event respectively. Based on the computed CAR values and t-values, the acceptance or rejection of the null hypothesis is shown in Tables VII and VIII. The detailed inferences, based on these results are presented in Section 4D.

D. Inferences

In this section, detailed conclusions, drawn from the results tabled in Section 4C, are presented. For each event, we draw three inference tables, corresponding to the estimation window, event window, and the post-event window respectively for the event. Each inference table is designed to clearly depict not only the final conclusions about the impact of the event on each of the eight sectors, but also help us visualize the important parameters such as the amount of variation in the CAR values, t-values, null hypothesis acceptance, and rejection percentages, that form basis for a particular conclusion.

The basis for inferences is as follows.

A high acceptance percentage of the null hypothesis, low CAR variations, and a t-value between -1.96 and 1.96 indicate no impact of the event on the studied sector. The quantum of rejection percentage of the null hypothesis and the quantum of variations in CAR indicate that a proportionate impact on the sector being examined. t-values less than -1.96 indicate negative impact and t-values greater than 1.96 indicate positive impact of the event on the sector.

Tables IX - XI show the inferences for event 1, drawn from the Graphs of CAR variations, t-value variations (Figures 4, 5 respectively), and Tables I and II, that were presented in Section 4C. It can be noticed that only the Oil and Gas sector shows minimal impact before the lockdown announcement, i.e., in the estimation window, as can be seen from Table IX. This is directly in line with the inferences from the CAR Graph of event 1 (Figure 4).

During the lockdown (Table X), while the IT sector remained unaffected, the Automobile, Oil & Gas, and Bank sectors were negatively Impacted. Consumer and Goods and Real Estate sectors were very negatively Impacted. Pharma and Metal sectors were positively Impacted.

TABLE II. Results of the Hypothesis testing for Bank, Pharma, Consumer Goods, and Real Estate sectors for the first event

Event Timeline	Banks			Pharma			Consumer Goods			Real Estate		
	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis
(-30,0)	0.012163	0.198933	Accepted	-0.0413679	-0.6401273	Accepted	0.04708692	0.889522	Accepted	0.05984203	0.81852606	Accepted
(-25,0)	0.00069178	0.01244408	Accepted	0.01810575	0.32376815	Accepted	0.13302101	2.190865	Rejected	-0.0098815	-0.1186776	Accepted
(-20,0)	0.018114	0.362841	Accepted	-0.0795653	-1.5078994	Accepted	0.04136325	0.95701	Accepted	0.02219772	0.37186062	Accepted
(-15,0)	0.0015	0.034704	Accepted	-0.020533	-0.449336	Accepted	0.03549368	0.948249	Accepted	0.00054516	0.01054541	Accepted
(-10,0)	-0.00782	-0.22148	Accepted	-0.0367653	-0.9853762	Accepted	-0.0678861	-2.22125	Rejected	-0.0294357	-0.6973658	Accepted
(-5,0)	-0.02712	-1.08655	Accepted	0.04773004	1.80913206	Accepted	-0.1898051	-8.78294	Rejected	-0.0581736	-1.9490723	Accepted
(0,0)	-0.02712	-1.08655	Accepted	0.04389737	3.72050529	Rejected	-0.2399350	-24.8262	Rejected	-0.1577711	-11.819911	Rejected
(0,5)	-0.11704	-4.6889	Rejected	0.07995348	3.03051071	Rejected	-0.1974286	-9.13571	Rejected	-0.1961542	-6.5720273	Rejected
(0,10)	-0.13914	-3.94151	Rejected	0.2275177	6.0978769	Rejected	-0.1081872	-3.53992	Rejected	-0.2085037	-4.9396994	Rejected
(0,15)	-0.1263	-2.9214	Rejected	0.24690533	5.40316602	Rejected	-0.1429017	-3.81776	Rejected	-0.215115	-4.1611365	Rejected
(0,20)	-0.1504	-3.01262	Rejected	0.2882314	5.46247874	Rejected	-0.1707777	-3.95124	Rejected	-0.2708036	-4.5365555	Rejected
(0,25)	-0.18276	-3.27445	Rejected	0.24575506	4.16577625	Rejected	-0.2059376	-4.2617	Rejected	-0.3291361	-4.9316504	Rejected
(0,30)	-0.20318	-3.32304	Rejected	0.24866368	3.84782398	Rejected	-0.2170702	-4.10069	Rejected	-0.315195	-4.3112732	Rejected

Figure 8. Graphs showing the CAR value of the eight sectors for the third event

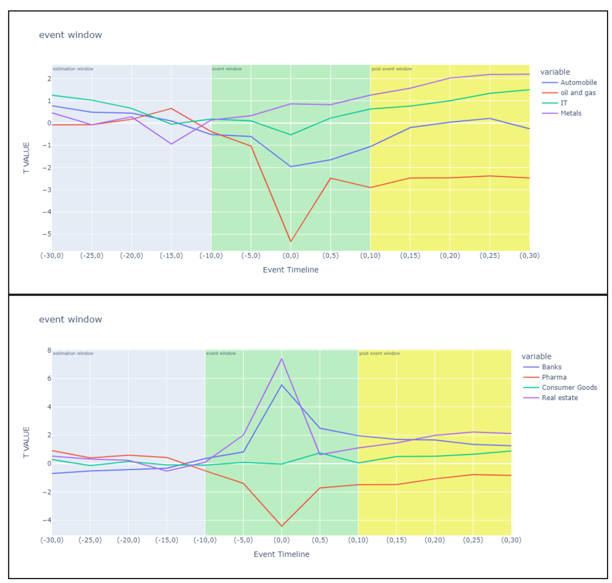

Figure 9. Graphs showing the t-value of each eight sector for the third event

Just after some days of the lockdown announcement, i.e., in the post-event window (Table XI), the lockdown

TABLE III. Results of the Hypothesis testing for Automobile, IT, Oil Gas and Metals sectors for the second event

Event Timeline	Automobile			IT			Oil & Gas			Metals		
	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis
(-30,0)	-0.06936	-0.39591	Accepted	-0.0333478	-0.018294	Accepted	-0.08461	-0.49301	Accepted	0.013597	0.075096	Accepted
(-25,0)	-0.08809	-0.5491	Accepted	-0.0161047	-0.0105338	Accepted	-0.03864	-0.24585	Accepted	-0.06095	-0.36757	Accepted
(-20,0)	-0.06484	-0.44969	Accepted	0.00231074	0.00187126	Accepted	0.043666	0.30915	Accepted	-0.01619	-0.10867	Accepted
(-15,0)	-0.07783	-0.61846	Accepted	0.00158101	0.00168042	Accepted	0.033153	0.268901	Accepted	-0.04346	-0.33413	Accepted
(-10,0)	-0.00879	-0.08427	Accepted	-0.0076805	-0.0118741	Accepted	0.010157	0.099358	Accepted	0.018737	0.173725	Accepted
(-5,0)	0.008969	0.116377	Accepted	0.04496211	0.12743788	Accepted	0.016761	0.221998	Accepted	0.021885	0.274747	Accepted
(0,0)	0.036049	1.145762	Accepted	0.00150855	0.0256544	Accepted	0.089438	2.901701	Rejected	0.078604	2.417175	Rejected
(0,5)	0.034574	0.448609	Accepted	0.00785475	0.02226303	Accepted	0.152843	2.024428	Rejected	0.100182	1.257702	Accepted
(0,10)	0.047625	0.456394	Accepted	-2.93E-05	-0.0000453	Accepted	0.145394	1.422264	Accepted	0.088905	0.824317	Accepted
(0,15)	0.04497	0.35732	Accepted	-0.0424931	-0.0451649	Accepted	0.207711	1.684733	Accepted	0.109417	0.841179	Accepted
(0,20)	0.035732	0.247825	Accepted	-0.0262068	-0.0212226	Accepted	0.201074	1.423564	Accepted	0.090104	0.604642	Accepted
(0,25)	0.072407	0.451328	Accepted	-0.0214819	-0.0140508	Accepted	0.241582	1.537122	Accepted	0.090414	0.545274	Accepted
(0,30)	0.059867	0.341748	Accepted	-0.0063955	-0.0035085	Accepted	0.237739	1.38532	Accepted	0.119915	0.662307	Accepted

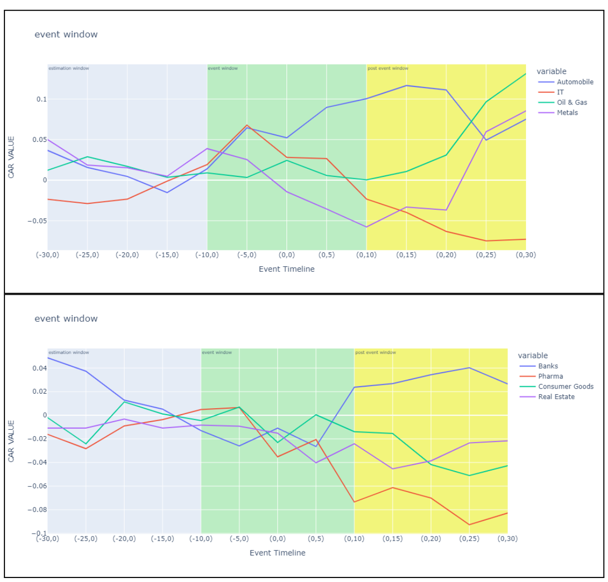

Figure 10. Graphs showing the CAR value of the eight sectors for the fourth event.

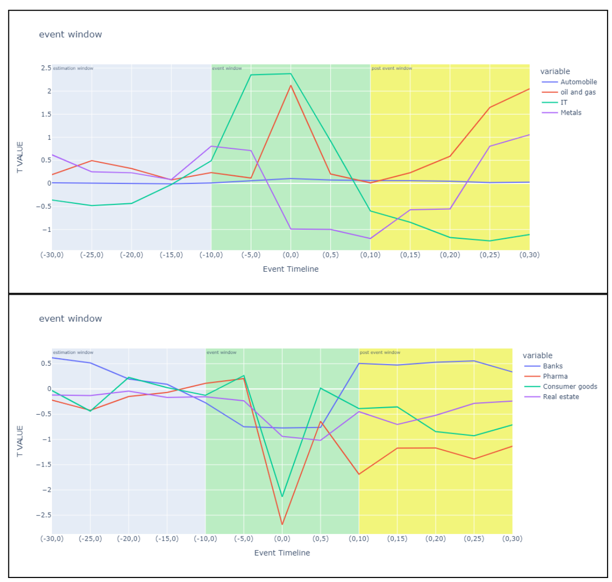

Figure 11. Graphs showing the t-value of the eight sectors for the fourth event

announcement ceases to affect the Automobile, IT, and Metal sectors. Consumer Goods and Bank sectors were negatively Impacted. The Real Estate sector still remains very negatively Impacted. The oil Gas sector shows

TABLE IV. Results of the Hypothesis testing for Bank, Pharma, Consumer Goods, and Real Estate sectors for the second event

Event Timeline	Banks			Pharma			COnsumer Goods			Real Estate		
	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis
(-30,0)	-0.0004018	-0.0021302	Accepted	0.07625232	0.49610765	Accepted	0.01569809	0.10217226	Accepted	-0.0074835	-0.0440405	Accepted
(-25,0)	0.01122015	0.06495601	Accepted	0.0591652	0.42032323	Accepted	0.00994682	0.07069105	Accepted	-0.0018924	-0.0121606	Accepted
(-20,0)	0.01349327	0.08691906	Accepted	0.00211446	0.01671451	Accepted	0.06995141	0.55316386	Accepted	-0.0289584	-0.2070593	Accepted
(-15,0)	-0.0072304	-0.0533589	Accepted	0.0248563	0.22510241	Accepted	-0.0297191	-0.2692421	Accepted	-0.0555149	-0.4547565	Accepted
(-10,0)	-0.0096338	-0.0857451	Accepted	-0.0116327	-0.1270533	Accepted	-0.0028828	-0.0314981	Accepted	-0.0119538	-0.1180969	Accepted
(-5,0)	-0.0731026	-0.8809769	Accepted	0.03233956	0.47825789	Accepted	0.00130206	0.019263	Accepted	-0.0404982	-0.5417385	Accepted
(0,0)	-0.0189307	-0.5588238	Accepted	-0.013035	-0.4721882	Accepted	0.11781645	4.26945941	Rejected	0.0248229	0.81335868	Accepted
(0,5)	0.009727	0.11722243	Accepted	-0.0360868	-0.5336742	Accepted	0.15978978	2.36396102	Rejected	0.09652475	1.29119738	Accepted
(0,10)	-6.93E-05	-0.0006168	Accepted	-0.0268176	-0.2929054	Accepted	0.12549574	1.37119622	Accepted	0.1230606	1.21577234	Accepted
(0,15)	0.03691546	0.27243051	Accepted	-0.0501176	-0.453873	Accepted	0.16598954	1.50379169	Accepted	0.17300251	1.41717015	Accepted
(0,20)	0.03040303	0.19584595	Accepted	-0.0750012	-0.5928737	Accepted	0.16837709	1.33149733	Accepted	0.13361748	0.95539552	Accepted
(0,25)	0.02755913	0.15954612	Accepted	-0.1404972	-0.9981247	Accepted	0.22077279	1.5690104	Accepted	0.13615887	0.87496128	Accepted
(0,30)	0.02812092	0.14909258	Accepted	-0.1388271	-0.9032271	Accepted	0.20626315	1.34247975	Accepted	0.11673022	0.68696095	Accepted

a bounce back by signaling a positive impact and the Pharma sector was very positively Impacted. Again, these observations are in line with the inferences from the CAR Graph of event 1 (Figure 4).

Tables XII-XIV show the inferences for event 2, drawn from the Graphs of CAR variations, t-value variations (Figures 6 and 7 respectively), and Tables III and IV, that were presented in results of the event-based empirical study (Section 4C). The basis for inference remains the same as detailed for the inferences of Event 1.

No sector shows the sign of being much Impacted during the estimation/event/post-event window period for the first unlock announcement (Table XII – XIV). This is in line with the inferences drawn from the CAR Graphs (Figure 6). It is interesting to note that while CAR Graphs document even small variations to the normal returns of the stock market sectors, a t-test labels only the large CAR variations, with t-values greater than 1.96 and t-values smaller than -1.96 as a significant impact. So, despite some CAR variations in IT and Pharma, these sectors are marked as not impacted. The sentimental analysis inferences explained in Section 5B (Figure 13) however show an increase in positivity for both IT and Pharma sectors.

Tables XV - XVII show the inferences for event 3, drawn from the Graphs of CAR variations, t-value variations (Figures 8 and 9 respectively), and Tables V and VI, that were presented in results of the event-based empirical study (Section 4C). The basis for inference remains the same as detailed for the inferences of event 1 and event 2. No sector shows the sign of being much Impacted during the estimation window period for the last unlock announcement (Table XV).

In some days after the final unlock announcement (Table XVII), the IT sector continues to be negatively impacted. Very low positive impact can still be seen on the Real Estate and Bank sectors. The remaining sectors still continue to remain unaffected in the post-event window.

Tables XVIII-XX show the inferences for event 4, drawn from the Graphs of CAR variations, t-value variations (Figures 10 and 11 respectively), and Tables VII and VIII, that were presented in results of the event-based empirical study (Section 4C). The basis for inference remains the same as detailed for the inferences of event 1 - event 3. No sector shows the sign of being much impacted by the vaccination announcement during the estimation/event/ window period except the IT sector, which shows a

TABLE V. Results of the Hypothesis testing for Automobile, IT, Oil Gas and Metals sectors for the third event

Event Timeline	Automobile			IT			Oil & Gas			Metals		
	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis
(-30,0)	0.053086	0.776116	Accepted	-0.0057206	-0.0796859	Accepted	0.0827	1.25078519	Accepted	0.03642966	0.45927635	Accepted
(-25,0)	0.030402	0.485328	Accepted	-0.0048431	-0.0736649	Accepted	0.0623658	1.02995414	Accepted	-0.0052615	-0.0724303	Accepted
(-20,0)	0.025048	0.44493	Accepted	0.01002529	0.16967121	Accepted	0.0359369	0.66037245	Accepted	0.01823122	0.27925825	Accepted
(-15,0)	0.004522	0.092029	Accepted	0.03382662	0.6558723	Accepted	-0.0023994	-0.0505118	Accepted	-0.0537874	-0.9438874	Accepted
(-10,0)	-0.02105	-0.51675	Accepted	-0.0164047	-0.3836118	Accepted	0.00711258	0.18058788	Accepted	0.00647994	0.13714333	Accepted
(-5,0)	-0.01813	-0.60242	Accepted	-0.0326466	-1.0336713	Accepted	0.00296066	0.10178209	Accepted	0.01145887	0.32837197	Accepted
(0,0)	-0.02406	-1.95832	Accepted	-0.068708	-5.3287843	Rejected	-0.0062948	-0.5300757	Accepted	0.01234188	0.86632535	Accepted
(0,5)	-0.04975	-1.6532	Accepted	-0.0782678	-2.4781523	Rejected	0.00651563	0.22399511	Accepted	0.02881172	0.82564497	Accepted
(0,10)	-0.04312	-1.05835	Accepted	-0.124029	-2.9003273	Rejected	0.02502563	0.63539933	Accepted	0.05949555	1.2591804	Accepted
(0,15)	-0.01001	-0.20369	Accepted	-0.127197	-2.4662524	Rejected	0.03601556	0.75820785	Accepted	0.08937933	1.56847263	Accepted
(0,20)	0.002337	0.041508	Accepted	-0.1456011	-2.464199	Rejected	0.05466497	1.0045176	Accepted	0.13214426	2.02413041	Rejected
(0,25)	0.013109	0.209266	Accepted	-0.15648	-2.3800865	Rejected	0.08078714	1.33417754	Accepted	0.15865086	2.18401491	Rejected
(0,30)	-0.01758	-0.25699	Accepted	-0.1772759	-2.4693887	Rejected	0.09930651	1.50194805	Accepted	0.17424715	2.19677054	Rejected

little bounce back from its status during event 3 (unlock announcement) (Tables XVIII-XX).

5. Sentimental Perspectives

Sentiment analysis, also sometimes known as opinion mining, is a branch of natural language processing (NLP) that has been extensively used in a large number of diverse applications to identify the polarity of sentiments expressed in textual corpora. The motivation is to be able to analyze and hence understand user's opinions, their sentiments, attitudes, and emotions. Many organizations and businesses have used this understanding to guide their policies, decisions, and products [20]. Sentiment analysis has been applied to understand the linkages between perception about Turkish universities and their academic success [21].

In the last two decades, social media has emerged as a very significant platform for users to freely express their thoughts and emotions. Micro blogging services such as Twitter allow users to express their opinion through tweets, which are pieces of information, limited in size to 140 characters. A large corpus of machine learning research has vetted the efficacy of sentiment analysis pursuits on Twitter, because of its wide popularity and hence wider audience [22]. Lately, therefore, a plethora of sentiment analytical studies have been conducted on Twitter [20, 23, 24, 25, 26]. For instance, prediction of the success of a movie based upon the sentiment analysis of related tweets has been taken up by [25, 26].

The study of stock markets using sentiment analysis has also inspired a lot of works [14, 27, 28, 29, 30] that firmly establish the fact that stock market trends are affected by the sentiments of investors. However, a majority of these works have focused on the prediction of stock prices. In this study we deploy the microblogging platform Twitter to extract COVID-19 related tweets, pertaining to the Indian stock market and perform sentiment analysis to analyze and understand the general sentiment of people towards the market in order to complement the event-based statistical study performed in the previous section. The extraction and preprocessing of tweets are detailed in Section 3B.

A. *Phases for Sentiment Analysis Mapping to the Event-Based Study.*

The sentiment analysis was conducted for approximately 1 year 4 months, in the following four contiguous phases: pre-COVID-19 phase (01 Nov 2019 – 24 March 2020), lockdown phase (24 March 2020 – 29 May 2020), unlock phase (29 May 2020 – 15 Jan 2021), and the vaccination phase (15 Jan 2021 – 22 Feb 2021).

TABLE VI. Results of the Hypothesis testing for Bank, Pharma, Consumer Goods, and Real Estate sectors for the third event

Event Timeline	Banks			Pharma			COnsumer Goods			Real Estate		
	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis
(-30,0)	-0.0578896	-0.6964021	Accepted	0.070668	0.921922	Accepted	0.01781972	0.2903711	Accepted	0.047266	0.52821	Accepted
(-25,0)	-0.0390844	-0.5134015	Accepted	0.028171	0.401301	Accepted	-0.0077996	-0.1387777	Accepted	0.025869	0.31567	Accepted
(-20,0)	-0.0290223	-0.4241914	Accepted	0.037752	0.598388	Accepted	0.0073272	0.14506473	Accepted	0.017237	0.234042	Accepted
(-15,0)	-0.0192204	-0.321842	Accepted	0.023932	0.434577	Accepted	-0.0040685	-0.0922805	Accepted	-0.03372	-0.52455	Accepted
(-10,0)	0.0178925	0.36133904	Accepted	-0.02292	-0.50206	Accepted	-0.0039595	-0.1083121	Accepted	0.005206	0.097672	Accepted
(-5,0)	0.03010608	0.82322546	Accepted	-0.04688	-1.39017	Accepted	0.00244413	0.09052792	Accepted	0.079572	2.021275	Rejected
(0,0)	0.08286153	5.55000183	Rejected	-0.06062	-4.40286	Rejected	-0.0003294	-0.0298823	Accepted	0.118913	7.398921	Rejected
(0,5)	0.09122672	2.49451789	Rejected	-0.05778	-1.71341	Accepted	0.02037868	0.75480342	Accepted	0.024856	0.631384	Accepted
(0,10)	0.0974812	1.96863334	Rejected	-0.06779	-1.48474	Accepted	0.00210669	0.05762853	Accepted	0.058907	1.105127	Accepted
(0,15)	0.10189787	1.70626031	Accepted	-0.08143	-1.47862	Accepted	0.02199741	0.49893603	Accepted	0.093935	1.461188	Accepted
(0,20)	0.11436282	1.67153469	Accepted	-0.06764	-1.07208	Accepted	0.02608439	0.51642167	Accepted	0.14699	1.995804	Rejected
(0,25)	0.10345883	1.35900497	Accepted	-0.05424	-0.7727	Accepted	0.03732886	0.66418859	Accepted	0.182979	2.232823	Rejected
(0,30)	0.10461798	1.25853604	Accepted	-0.06373	-0.8314	Accepted	0.05451284	0.88828296	Accepted	0.190266	2.126283	Rejected

Section 5B presents the results from the sentimental study of the tweets for the eight stock market sectors understudy, for the phases stated above. Inferences drawn from these results are also presented alongside.

Figure 12 presents a mapping of these sentimental analysis phases to the four events and their corresponding event windows for corroboration of results and inferences presented in Section 5B with the results presented in Section 4C and the inferences presented in Section 4D.

B. *Results & Inferences*

Figure 13 depicts the sentimental analysis in terms of the percentage of positive, negative, and neutral sentiments for four different phases i.e., pre-COVID-19, lockdown, unlock, and vaccination phase. The first row shows the sentimental analysis for the IT sector and the second row shows the sentiment analysis for the Pharma sector respectively.

Despite small variations, the overall sentiment of people remains positive or neutral towards the IT sector, except for the unlock phase. This may be due to the increased reliance of people on IT tools and services for both professional and day-to-day personal tasks. The hope of a normal work environment and lifestyle in the vaccination phase may signal low reliance of people on IT services and hence the decrease in positivity. People's fear and reliance on medicines seem to dictate their sentiment behind the Pharma sector. As can be seen from the Figure, the sentiment becomes highly positive during the transition from the pre-COVID to lockdown phase. In the unlock and vaccination phases, as the people step out of their homes and the fear factor goes down the reliance on the Pharma and hence its positivity rate decreases.

Figure 14 depicts the sentimental analysis for four different phases i.e., pre-COVID-19, lockdown, unlock, and vaccination phase. The first row shows the sentimental analysis of the Real Estate sector and the second row shows the sentiment analysis for the Bank sector respectively.

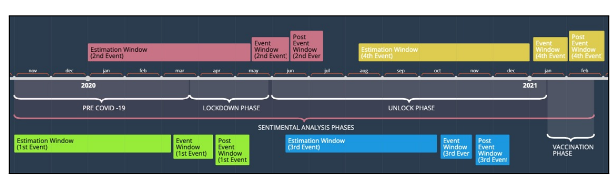

Figure 12. Mapping of Sentimental Analysis phases and Event Windows of the Four Events

Real Estate, treated as a symbol of financial security in Indian society, retained the interest of people during all

TABLE VII. Results of the Hypothesis testing for Automobile, IT, Oil & Gas and Metals sectors for the fourth event

Event Timeline	Automobile			IT			Oil & Gas			Metals		
	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis
(-30,0)	0.036668	0.013128	Accepted	-0.02362	-0.36006	Accepted	0.01222277	0.19091604	Accepted	0.0500971	0.61891471	Accepted
(-25,0)	0.015612	0.006104	Accepted	-0.02889	-0.48099	Accepted	0.02894033	0.4935948	Accepted	0.01858313	0.25068666	Accepted
(-20,0)	0.004594	0.001999	Accepted	-0.02343	-0.43396	Accepted	0.01696171	0.32189464	Accepted	0.01529206	0.22953848	Accepted
(-15,0)	-0.01538	-0.00767	Accepted	-0.00121	-0.02561	Accepted	0.00353632	0.07688559	Accepted	0.00481167	0.08274365	Accepted
(-10,0)	0.013805	0.008298	Accepted	0.019176	0.490747	Accepted	0.0089259	0.23405037	Accepted	0.03888834	0.80653302	Accepted
(-5,0)	0.064529	0.052516	Accepted	0.067894	2.352656	Rejected	0.0032825	0.11654225	Accepted	0.02535214	0.71193113	Accepted
(0,0)	0.052251	0.104161	Accepted	0.028034	2.379493	Rejected	0.02443714	2.12522098	Rejected	-0.0143663	-0.9881961	Accepted
(0,5)	0.08977	0.073058	Accepted	0.026498	0.918218	Accepted	0.00573777	0.20371431	Accepted	-0.0355618	-0.998637	Accepted
(0,10)	0.100436	0.060367	Accepted	-0.02334	-0.59724	Accepted	0.00042046	0.011025	Accepted	-0.057616	-1.1949392	Accepted
(0,15)	0.116606	0.058113	Accepted	-0.039760	-0.84362	Accepted	0.01060979	0.23067501	Accepted	-0.0331696	-0.5704004	Accepted
(0,20)	0.111211	0.048378	Accepted	-0.06327	-1.17195	Accepted	0.03099661	0.58824509	Accepted	-0.0368382	-0.552952	Accepted
(0,25)	0.049344	0.019291	Accepted	-0.07485	-1.24593	Accepted	0.09655764	1.64684863	Accepted	0.05972507	0.80569207	Accepted
(0,30)	0.075051	0.026871	Accepted	-0.0728	-1.10988	Accepted	0.13130745	2.05098378	Rejected	0.08544398	1.05560077	Accepted

Figure 13. Sentimental analysis for four different phases of IT sector and Pharma sector respectively

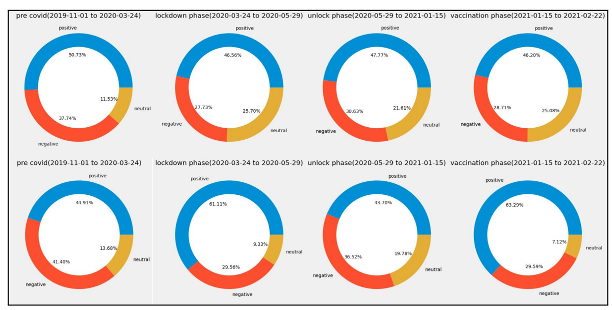

Figure 14. Sentimental analysis for four different phases of Real Estate and Banking sectors respectively

phases and even increased during the vaccination phase. A part of this sustained interest is due to the digital upgradation of India's Real Estate sector by the introduction of virtual reality site visits, chatbot-assisted query answering and online bookings, etc. A lot of Real Estate deals have taken place remotely, online. The Bank sector, with lower rates of interest on savings and deposit accounts than before and hence low Consumer and corporate confidence, saw a sustained decline in the positivity after the pre-COVID phase.

Figure 15 depicts the sentimental analysis for the Consumer Goods in the first row and the Metals sector in the second-row sector respectively. The Consumer Goods mirror a predictable sentiment. As the people got locked in their homes, their requirement for new items such as clothes, new household goods, and jewelry, etc. declined and hence the declining positive sentiment is shown in the figure. After an initial jump in the lockdown phase, the Metals sector shows a decline in the unlock and vaccination phases mainly due to operational difficulties, worker absenteeism, and poor demand especially from the construction sector, which is one of the major end-users of

TABLE VIII. Results of The Hypothesis Testing For Bank, Pharma, Consumer Goods And Real Estate Sectors For The Fourth Event

Event Timeline	Banks			Pharma			Consumer Goods			Real Estate		
	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis	CAR	t-value	Acceptance/ Rejection of the Null Hypothesis
(-30,0)	0.04867756	0.61678844	Accepted	-0.0161723	-0.2217659	Accepted	-0.0019573	-0.0325971	Accepted	-0.0108737	-0.1210528	Accepted
(-25,0)	0.03730391	0.51612623	Accepted	-0.0282985	-0.4237223	Accepted	-0.024189	-0.4398763	Accepted	-0.010827	-0.1316131	Accepted
(-20,0)	0.01278862	0.19688031	Accepted	-0.0090048	-0.1500264	Accepted	0.01132381	0.22912995	Accepted	-0.0032697	-0.0442263	Accepted
(-15,0)	0.00520548	0.09180989	Accepted	-0.0036695	-0.0700409	Accepted	0.00112695	0.02612433	Accepted	-0.0108814	-0.1686177	Accepted
(-10,0)	-0.0129067	-0.2745399	Accepted	0.00483915	0.11139786	Accepted	-0.004456	-0.1245791	Accepted	-0.0083187	-0.1554663	Accepted
(-5,0)	-0.0260046	-0.7489684	Accepted	0.00656302	0.2045655	Accepted	0.00694719	0.26298588	Accepted	-0.0092765	-0.2347398	Accepted
(0,0)	-0.0109405	-0.7718392	Accepted	-0.0352172	-2.6888082	Rejected	-0.0230228	-2.134804	Rejected	-0.0151501	-0.9390577	Accepted
(0,5)	-0.0264706	-0.7623887	Accepted	-0.0205811	-0.6415009	Accepted	0.00040322	0.01526378	Accepted	-0.0402184	-1.0177167	Accepted
(0,10)	0.0237241	0.50463941	Accepted	-0.0734146	-1.6900143	Accepted	-0.0139003	-0.3886205	Accepted	-0.024091	-0.4502318	Accepted
(0,15)	0.02684681	0.47350106	Accepted	-0.0613306	-1.170636	Accepted	-0.0153611	-0.3560915	Accepted	-0.0453467	-0.7026906	Accepted
(0,20)	0.03433881	0.52864468	Accepted	-0.0701011	-1.1679368	Accepted	-0.0417165	-0.8441063	Accepted	-0.0386197	-0.5223685	Accepted
(0,25)	0.04023765	0.55671669	Accepted	-0.0926997	-1.3880214	Accepted	-0.0510072	-0.9275633	Accepted	-0.0234321	-0.284841	Accepted
(0,30)	0.02654478	0.33634622	Accepted	-0.0827863	-1.1352248	Accepted	-0.0426909	-0.7109741	Accepted	-0.0216649	-0.2411867	Accepted

TABLE IX. Inference Table for Estimation window of Event 1

Estimation Window for Event 1					
Sector	Variation in CAR: (No/ Small/ Large)	Null Hypothesis Acceptance percentage (%)	Null Hypothesis Rejection percentage (%)	t-value	Final Conclusion
Automobile	Small	100	0	-0.2846996	Not Impacted
IT	Small	100	0	-0.07080038	Not Impacted
Pharma	Small	100	0	-0.89697466	Not Impacted
Oil & Gas	Large	20	80	1.986642	Small positive Impact
Consumer Goods	Small	80	20	0.3616956	Not Impacted
Real Estate	Small	100	0	0.150352502	Not Impacted
Metals	Small	100	0	0.107430432	Not Impacted
Banks	Small	100	0	0.0693736	Not Impacted

TABLE X. Inference Table for Event window of Event 1

Event Window for Event 1					
Sector	Variation in CAR: (No/ Small/ Large)	Null Hypothesis Acceptance percentage (%)	Null Hypothesis Rejection percentage (%)	t-value	Final Conclusion
Automobile	Large	60	40	-2.48960376	Negatively Impacted
IT	Small	80	20	-1.56140706	Not Impacted
Pharma	Large	40	60	2.734529752	Positively Impacted
Oil & Gas	Large	20	80	-2.3579876	Negatively Impacted
Consumer Goods	Large	0	100	-9.701204	Highly Negatively Impacted
Real Estate	Large	60	40	-5.19561516	Highly Negatively Impacted
Metals	Large	60	40	3.529264114	Positively Impacted
Banks	Large	60	40	-2.204998	Negatively Impacted

the Metals in India.

Figure 15. Sentimental analysis for four different phases for Consumer Goods and Metal Sectors respectively.

Figure 16 depicts the sentimental analysis for the Oil & Gas and Automobile sectors in the first and second-row sectors respectively. Oil and Gas being essential commodities, figured positively in people's sentiments, as expected. The decline of usage and sale of Automobiles fueled the proportionate decline in the peoples' sentiment for the Automobile sector, as seen in the figure.

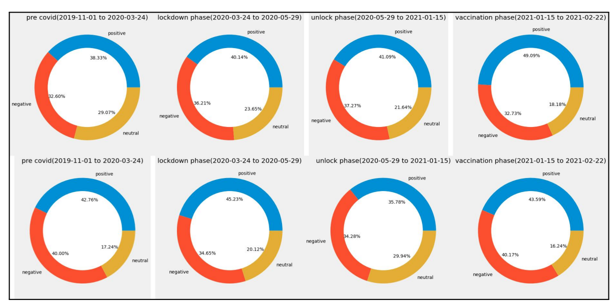

Figure 16. Sentimental analysis for four different phases for Oil & Gas and Automobile Sectors respectively

6. Conclusions and Future Directions

This paper proposed a twin impact model to study, both statistically and sentimentally, the impact of the COVID-19 pandemic on eight Indian stock market sectors. Four events, namely, the announcement of the first lockdown, the announcement of the first partial unlock, the last unlock announcement, and the first day of vaccination were chosen for a little over one year. The Market model was employed and the concepts of cumulative abnormal returns

TABLE XI. Inference Table for Post Event window of Event 1

Post Event Window for Event 1					
Sector	Variation in CAR: (No/ Small/ Large)	Null Hypothesis Acceptance percentage (%)	Null Hypothesis Rejection percentage (%)	t-value	Final Conclusion
Automobile	Small	100	0	-0.448460708	Not Impacted
IT	Small	100	0	-0.94513414	Not Impacted
Pharma	Small	0	100	4.995424378	High Positive Impact
Oil & Gas	Large	0	100	3.1778468	Positive Impact
Consumer Goods	Small	0	100	-3.934262	Negative Impact
Real Estate	Large	0	100	-4.576063	High Negative Impact
Metals	Small	100	0	0.859573508	Not Impacted
Banks	Large	0	100	-3.294604	Negative Impact

TABLE XII. Inference Table for Estimation window of Event 2

Estimation Window for Event 2					
Sector	Variation in CAR (No/ Small/ Large)	Null Hypothesis Acceptance percentage (%)	Null Hypothesis Rejection percentage (%)	t-value	Final Conclusion
Automobile	Large	100	0	-0.419486	Not Impacted
IT	Small	100	0	-0.007430044	Not Impacted
Pharma	Large	100	0	0.2062389	Not Impacted
Oil & Gas	Large	100	0	-0.0122902	Not Impacted
Consumer Goods	Small	100	0	0.085057394	Not Impacted
Real Estate	Small	100	0	-0.16722276	Not Impacted
Metals	Small	100	0	-0.1123098	Not Impacted
Banks	Small	100	0	0.002128174	Not Impacted

TABLE XIII. Inference Table for Event window of Event 2

Event Window for Event 2					
Sector	Variation in CAR: (No/ Small/ Large)	Null Hypothesis Acceptance percentage (%)	Null Hypothesis Rejection percentage (%)	t-value	Final Conclusion
Automobile	Small	100	0	0.4165744	Not Impacted
IT	Small	100	0	0.032687182	Not Impacted
Pharma	Small	100	0	-0.189512642	Not Impacted
Oil & Gas	Large	60	40	1.3339498	Not Impacted
Consumer Goods	Large	60	40	1.59847631	Not Impacted
Real Estate	Large	100	0	0.5320986	Not Impacted
Metals	Large	80	20	0.9895332	Not Impacted
Banks	Small	100	0	-0.281788034	Not Impacted

TABLE XIV. Inference Table for Post Event window of Event 2

Post Event Window for Event 2					
Sector	Variation in CAR: (No/ Small/ Large)	Null Hypothesis Acceptance percentage (%)	Null Hypothesis Rejection percentage (%)	t-value	Final Conclusion
Automobile	Small	100	0	0.370923	Not Impacted
IT	Small	100	0	-0.01679842	Not Impacted
Pharma	Large	100	0	-0.64820078	Not Impacted
Oil & Gas	Large	100	0	1.4906006	Not Impacted
Consumer Goods	Large	100	0	1.423595078	Not Impacted
Real Estate	Small	100	0	1.030052048	Not Impacted
Metals	Small	100	0	0.6955438	Not Impacted
Banks	Small	100	0	0.155259672	Not Impacted

TABLE XV. Inference Table for Estimation window of Event 3

Estimation Window for Event 3					
Sector	Variation in CAR: (No/ Small/ Large)	Null Hypothesis Acceptance percentage (%)	Null Hypothesis Rejection percentage (%)	t-value	Final Conclusion
Automobile	Small	100	0	0.2563306	Not Impacted
IT	Small	100	0	0.057716182	Not Impacted
Pharma	Large	100	0	0.3708256	Not Impacted
Oil & Gas	Small	100	0	0.614237572	Not Impacted
Consumer Goods	Small	100	0	0.019213106	Not Impacted
Real Estate	Large	100	0	0.1302088	Not Impacted
Metals	Large	100	0	-0.028127954	Not Impacted
Banks	Large	100	0	-0.318899592	Not Impacted

TABLE XVI. Inference Table for Event window of Event 3

Event Window for Event 3					
Sector	Variation in CAR: (No/ Small/ Large)	Null Hypothesis Acceptance percentage (%)	Null Hypothesis Rejection percentage (%)	t-value	Final Conclusion
Automobile	Small	60	40	-1.157808	Not Impacted
IT	Large	40	60	-2.4249094	Negative Impact
Pharma	Large	80	20	-1.898648	Not Impacted
Oil & Gas	Small	100	0	0.122337742	Not Impacted
Consumer Goods	Small	100	0	0.152953094	Not Impacted
Real Estate	Large	60	40	2.2508758	Positive Impact
Metals	Small	100	0	0.683333204	Not Impacted
Banks	Large	40	60	2.239543512	Impacted

TABLE XVII. Inference Table for Post Event window of Event 3

Post Event Window for Event 3					
Sector	Variation in CAR: (No/ Small/ Large)	Null Hypothesis Acceptance percentage (%)	Null Hypothesis Rejection percentage (%)	t-value	Final Conclusion
Automobile	Small	100	0	-0.2536512	Not Impacted
IT	Large	0	100	-2.53605078	Negative Impact
Pharma	Small	100	0	-1.127908	Not Impacted
Oil & Gas	Large	100	0	1.046850074	Not Impacted
Consumer Goods	Small	100	0	0.525091556	Not Impacted
Real Estate	Large	80	20	1.784245	Very Low Positive Impact
Metals	Large	80	20	1.846513778	Very Low Positive Impact
Banks	Small	80	20	1.59279387	Not Impacted

TABLE XVIII. Inference Table for Estimation Window for Event 4

Estimation Window for Event 4					
Sector	Variation in CAR: (No/ Small/ Large)	Null Hypothesis Acceptance percentage (%)	Null Hypothesis Rejection percentage (%)	t-value	Final Conclusion
Automobile	Small	100	0	0.0043718	Not Impacted
IT	Large	100	0	-0.1619746	Not Impacted
Pharma	Large	100	0	-0.150831528	Not Impacted
Oil & Gas	Small	100	0	0.263468288	Not Impacted
Consumer Goods	Large	100	0	-0.068359644	Not Impacted
Real Estate	Small	100	0	-0.12419524	Not Impacted
Metals	Small	100	0	0.397683304	Not Impacted
Banks	Large	100	0	0.229412994	Not Impacted

TABLE XIX. Inference Table for Event Window for Event 4

Event Window for Event 4					
Sector	Variation in CAR: (No/ Small/ Large)	Null Hypothesis Acceptance percentage (%)	Null Hypothesis Rejection percentage (%)	t-value	Final Conclusion
Automobile	Large	100	0	0.05968	Not Impacted
IT	Large	60	40	1.7087748	Very Low & Positive Impact
Pharma	Large	80	20	-0.940872008	Not Impacted
Oil & Gas	Small	80	20	0.538110582	Not Impacted
Consumer Goods	Large	80	20	-0.473950788	Not Impacted
Real Estate	Large	100	0	-0.55944246	Not Impacted
Metals	Large	100	0	-0.33266163	Not Impacted
Banks	Small	100	0	-0.410619358	Not Impacted

TABLE XX. Inference Table for Post Event Window for Event 4

Post Event Window for Event 4					
Sector	Variation in CAR: (No/ Small/ Large)	Null Hypothesis Acceptance percentage (%)	Null Hypothesis Rejection percentage (%)	t-value	Final Conclusion
Automobile	Small	100	0	0.042604	Not Impacted
IT	Large	100	0	-0.993724	Not Impacted
Pharma	Large	100	0	-1.31036666	Not Impacted
Oil & Gas	Large	100	0	0.905555502	Not Impacted
Consumer Goods	Large	100	0	-0.64547114	Not Impacted
Real Estate	Small	100	0	-0.44026372	Not Impacted
Metals	Large	100	0	-0.091399752	Not Impacted
Banks	Small	100	0	0.479969612	Not Impacted

and two-tailed t-test were used to assess the impact of the aforementioned events on the eight stock market sectors chosen for study. To understand the general sentiment of people towards the market to compliment the event-based statistical study, sentiment analysis of COVID-19 related tweets, about the Indian stock market was performed. Detailed inferences of both the statistical and sentimental analysis were drawn over different time windows are drawn to aid manual corroboration of time-variant patterns and subjective inferences. The key stock market players may be benefited by studying the inferences presented in the paper, to have an idea of how the market responds to volatile situations and decisions taken by governments, during a pandemic like situation. The future work may include a comparison of the impact of identified events on different world economies. The study of the impact of different types of vaccines and vaccine-related misinformation on the stock market also promises to unfold interesting results.

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