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# A Computational Analysis of Financial Markets response to shock events - A case study on Covid 19 Pandemic

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# Declaration

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# Abstract

This research is an attempt to computationally analyze and explain the impact of a shock event on financial markets by studying the variance in stock market returns. Financial markets are complex marketplace for buying and selling of financial instruments, and the price of these instruments are influenced by several factors. Three key types of analysis, fundamental analysis in which a company's financial statements are studied, technical analysis in which flow of information related to a stock and its demand and supply in the market is believed to determine the price and finally behavioural analysis in which the investors are assumed to behave irrationally leading to hoarding at times of positive news and mass sell offs at times of panic, such as during Covid 19. Thus, a statistical approach is deployed to study if a relationship exists between shock event variable and stock returns over a period of two years from January 2020 to December 2021. Covid 19 pandemic is chosen the shock event of interest and daily infections along with log change in daily infections are selected as a proxy for the shock event. Three indexes from stable as well as emerging markets were selected as proxy for financial markets for this study, along with 14 individual firms of which five belong to Automobile, four to Pharmaceuticals, three to banking and two to IT sector. Using Panel study method, results from auto regression models build with shock variables are compared with auto regression models with 5 day lags of stock returns. While daily infections of Covid 19 was found to be not explanatory of the variance in returns for any of the 17 stocks, log change in daily infections of Covid 19 is found to be statistically significant for 3 out of the 17 stocks, that help in explaining the variability in stock returns during the Covid 19 period.

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# Nomenclature

API	Application Protocol Interface
WHO	World Health Organization
S&P500	Standard and Poor's 500
DJIA	Dow Jones Industrial Average
BSE	Bombay Stock Exchange
TTM	Tata Motors
TM	Toyota Motors
F	Ford
HMC	Honda Motors
GM	General Motors
AZN	AstraZeneca
PFE	Pfizer
MRNA	Moderna
RDY	Dr. Reddy's Laboratories
HDB	HDFC Bank
IBN	ICICI Bank
AXS	Axis Bank
WIT	Wipro
INFY	Infosys
USA	United States of America

# Chapter 1 - Introduction

Financial markets, a complex marketplace used for buying and selling of financial instruments, have been in existence for quite some time and people have been involved with it to invest, study the upward or downward market movements and realize profits from their investments. Studying these movements has never been easy task and ever so often, markets are effected by unprecedented information causing immediate rise or decline in prices. The mapping and study of effect of such shock events has been of interest to the scientific and trading community alike.

This chapter therefore provides the reader with an introduction of Financial markets and how they operate, along with a brief on methodologies employed by people to study it. Development and timelines around the Covid 19 pandemic, the scale and impact it had on the world is also covered, and finally moving to key objectives, findings and further layout of the thesis.

## 1.1 Background

### 1.1.1 Financial Markets

Buyers and sellers, who are also known as traders, have the option to engage in financial instrument trading on financial markets. These financial instruments include equities, commodities, currencies, bonds, and derivatives. Financial markets may be thought of as a market, a system, or a place. They act as a communications route between those who have the funds to invest and those who are in need of capital for various reasons. Since the 1600s, there have been similar marketplaces all over the world. When investors buy these assets, which reflect ownership in a firm, they do so with the intention of developing a plan to generate returns from their investment. Since that time, there has been a substantial uptick in interest regarding the investigation of these financial markets, how they function, and the phenomena that have an influence on them in order to understand the market and estimate the movement to gain excess profit from trading on the said markets or exchanges.

A range of theories have been proposed in an effort to explain how these markets function. The Efficient Market Hypothesis is a well-known example of this type of influential hypothesis. Fama [1970] proposed the Efficient Market Hypothesis, which states that all of the information that is necessary to determine the true value of an asset can be found in the price of that asset, and that the current price always accurately reflects all of the news that is currently available. If the traders or investors determine that the asset is undervalued, in which case they buy it, or if they determine that the asset is overvalued, in which case they sell it, and through this trade the traders or investors realize the new true price of the asset, which now accurately reflects the information that is available. Any new information that becomes publicly available after this point is then analyzed by traders or investors. On the basis of this idea, investors and stakeholders seek for opportunities in which fresh information has not been entirely included in the stock prices, in which there are price fluctuations, and in which there is the potential to beat the market by generating profit from excess returns. The reasons for these price shifts in financial assets might be a combination of a number of variables, including political upheavals, the supply and demand of instruments, significant events (such as war, natural catastrophes, and so on), and investor behavior.

Studying the effect of such events that disrupt the price of market equilibrium is thus of significant value to traders, investors and stakeholders, who can devise trading strategies to beat the market or stakeholders that can design better policies based on the study of event to withstand its effects, in the case of recurring events.

To understand the effects better of an event, Ball and Brown [1968] formulated the event study methodology, which states that by analysing abnormal returns or defined short or long term windows, one can extract the impact of the event on stock returns, which are defined as the log difference between adjusted closing price of a stock at day  $t$  and day  $t-1$ . The reason for choosing stock returns over daily prices is that daily prices are highly correlated with previous day prices, which makes statistical study of market prices more difficult. On the other hand, change in stock prices or stock returns have little to no correlation, which is evaluated later in the research, thus making the statistical study using stock returns easier. Along with that, stock returns are negative when current day price is lesser than previous day prices, positive when current day price is higher than previous day price and 0 if there is no change in prices, thus track the increase or decrease in prices.

Numerous such studies, based on event study methodology, have been done in the past to explore the impact of different events on stock markets across the world, such as Kowalewski and Śpiewanowski [2020] study the impact of natural and man made disasters, Shelor et al. [1990] research on earthquakes. Further, Bash and Alsaifi [2019] examine the effect of political upheavals, Chen and Siems [2004] and Karolyi and Martell [2006] study the effect of terrorist attacks.

### 1.1.2 Covid 19 Pandemic

While studies based on above mentioned events have a more localized impact on stocks, that is stock markets of the country in which such events happen are the ones that are impacted, spread of deadly diseases can be classified as events that spread around the world and have a much bigger impact. There have been several outbreaks in the past such as Avian Influenza in 1997, Severe Acute Respiratory Syndrome or SARS in 2003, Swine flu in 2009 to 2010, Ebola outbreak in 2014 to 2016 and Middle East Respiratory Syndrome or MERS outbreak in 2012.

One such event that happened recently is the Novel Coronavirus or Covid 19 pandemic. On December 31, 2019, cases of pneumonia detected in Wuhan, China, were first reported to the World Health Organization (WHO). On January 1, 2020, the Huanan Seafood Wholesale Market was closed after it was discovered that the wild animals sold there may be the source of the virus. The next day, January 2, 2020, was the first trading day after these occurrences and there was a gradual flow of new information. For instance, an ophthalmologist at Wuhan Central Hospital, alerted alumni from his medical school class about the advent of SARS coronavirus. This virus turned out to be the new coronavirus. On January 6, Hong Kong started screening passengers on trains that had stopped at Wuhan, and on the same day, the Centers for Disease Control and Prevention in the United States issued a warning that travelers to Wuhan should avoid contact with animals, animal markets, and people who are ill. (Ramelli and Wagner [2020])

Because the outbreak of the novel coronavirus began in Wuhan, which is located in Hubei Province and is one of the most significant transportation hubs in China, and because it occurred at the same time as the rush to travel for the Spring Festival, which is the largest annual mass migration of people that occurs anywhere in the world, the epidemic quickly became a national crisis. Zhong Nanshan, the chief of the high-level expert panel from the National Health and Fitness Commission of China, made the announcement on January 20, 2020, that the new coronavirus might be passed from person to person. This caused considerable anxiety and terror among the Chinese population. On January 31, 2020, the World Health Organization (WHO), for the sixth time ever, announced a public health emergency of international concern due to the unique coronavirus outbreak that was occurring in China (COVID-19). Recent examples include the Ebola and Zika virus epidemics that occurred in Africa (Khan et al. [2020]).

At a global level, the Global Risks Report that was released on January 15, 2020 said that the top five risks that the world may face in the long future are all related to environmental concerns, Researchers at the Wuhan Institute of Technology foresaw the likelihood of SARS-MERS type coronavirus epidemics, the "infectious illness" is put at number 10 in terms of its effect due to the rarity of its occurrence. A few weeks following the release of the World

Economic Forum's Global Risks Report, on March 11, the World Health Organization (WHO) announced that COVID-19 was a pandemic. The emergence of COVID-19 and its spread to more than 150 countries within two months brought to the attention of the world the fact that the disease is not only a medical health issue, but also halted the business and economic activities, and the outbreak could cause more severe threats to the global economy in the long run. (Khan et al. [2020])

More than 2 years later, Covid 19 is still prevalent with numerous variants throughout the world. Globally, it has affected 5.8+ million people and resulted in the deaths of 6.4+ million people, making it the deadliest virus to have engulfed the world. With such magnitude of losses around the world, this study aims to ascertain the impact the pandemic had on the financial markets over the course of first two years.

## 1.2 Objectives

This thesis aims to explore the effect of a major shock event such as Covid 19 pandemic on stock markets computationally, by taking into account the daily cases as a proxy for news or information flow regarding the event and statistically examining a causal relation between the financial markets and shock event. This is accomplished by the following two methods:

1. Investigating the relationship between daily cases of Covid 19 and daily returns series of stock markets using descriptive statistics and stylized facts.
2. Statistical inferences derived from cross sectional study of Auto regression models to establish if computational methods can ascertain the impact of shock event on stock price returns.

## 1.3 Key Findings

By using descriptive statistics on the transformed daily adjusted close price of the 17 indexes and firms as stock returns, the three stylized facts are confirmed over the period of two years from January 2020 to December 2021. The three stylized facts are as follows:

1. Daily Return series distribution is non-normal in nature
2. There is minimum or no auto correlation between returns and its nearby day lagged values. This is evaluated for a window of 30 day.
3. Transformed returns, specifically absolute and squared returns, have a positive dependence on its nearby day lagged values. This is also evaluated for a 30 day window.

Using exploratory data analysis techniques, it was found that all three index and 10 out of the 14 firms showed a negative response to the onset of Covid 19, with average returns lesser

than 0 for the first quarter of 2020, and then immediately bouncing back with positive average returns thereafter. Only the initial announcement of Covid 19 being declared as pandemic, country wide lockdowns and rise of cases around the world had a significant impact on the markets. From second quarter of 2020 onwards, markets had completely incorporated the information flow related to Covid 19, which is indicated by the fact that consistent rise in daily infections, deaths or roll out of vaccination had no impact on daily returns.

Next, volume of daily infections is used as a shock variable to map the impact of Covid 19 and it was found that for none of the 17 series considered, the shock variable was statistically significant, indicating that use of volume of daily infections is not a viable proxy to map the impact of a pandemic event. On the other hand, using log difference of daily infections as the shock variable was found to be statistically significant in 3 firms, two from pharmaceutical sector and one from Automobile sector, indicating that this transformed shock variable is relevant proxy for studying the impact of a pandemic and the computational model was able to ascertain the impact of the shock event.

## 1.4 Thesis Structure

Chapter 2 discusses in detail the topics introduced in this chapter, previous research that has been published in terms of what methodologies have been in use to evaluate shock event and their impact. It also critically evaluates the previous research that have been done around the subject, that is how different methodologies are deployed to study the relation between events and stock markets, and their merits. Chapter 3 introduces the methodology that has been adopted for this research, what models will be used and their theoretical background, along with their relevance to the research. Chapter 4 describes the case study and its implementation, and then discusses on the results obtained from methods deployed and the inferences that are derived from those results. Finally, Chapter 5 summarizes the research, which also covers any issues faced and future work that can be built on top of this research.

# Chapter 2 - Literature Review

This section aims to critically evaluate the research around Event study methodology to understand how it is used to study the impact of an event on the market and to develop the methodology based on the findings. Impact of various events, ranging from Natural Disasters, political events, terrorist attacks, epidemics and pandemics, on the stock markets around the world are explored. Along with that, this chapter also covers the motivation behind this research. The section is further divided into following sections:

1. Event Study Methodology
2. Study of Different Events and their impact
3. Motivation

## 2.1 Event Study Methodology

Research on financial markets has been largely guided by the efficient market hypothesis since it was first proposed. Fama [1970] theorized the idea behind this, that the price of a security reflects all of the information that is currently accessible on the market; as a result, investors are unable to make abnormal gains from their investments. Financial markets, like any other market, are driven by supply and demand, in this case of assets, and through buying and selling of these assets traders realize the value of these assets and an equilibrium of price is obtained. Whenever new information is made available to the buyers and sellers, they try to determine the new price based on the new information and depending on the interpretation of news, either start selling or buying at a new price till a new equilibrium of prices is established, thus incorporating the new information in the prices. These can be triggered as a result of major or shock events that have an unprecedented effect on the economy.

Study of major events impacting the stock markets has been of interest to the economists and traders for quite a while now. These events range from natural disasters, corporate announcements, political upheavals, terrorists attacks, spread of diseases, etc. Such events in history have been found to induce uncertainty in the investor's mind, causing them to behave



irrationally and result in sudden increase or decrease in prices of stock markets. Ball and Brown [1968] established the Event study methodology that has been in use to determine the impact of such events on stock markets. It uses financial market data to measure the impact of certain events on a company's value. The usefulness of such studies stems from the fact that, given market rationality, the effects of events are immediately reflected in the price of a security. A measure of the economic impact of an event can therefore be constructed from observed security prices over a relatively short period of time.

These studies focus on analyzing the impact of events on stock markets using event study methodology, which focuses on determining the impact on stock markets using event dependent windows and studying the abnormal and cumulative abnormal returns, that are defined as follows:

$$AR_t = R_t - \mu_R \quad (1)$$

$$CAR_t = \sum_{t=0}^n AR_t \quad (2)$$

Through this methodology, one can determine the abnormal returns during the event window however, it does not account for control or shock variable responsible for abnormal returns.

## 2.2 Study of Different Events and their impact

### 2.2.1 Disaster events and their impacts

Many researches have been since performed to study the effect of major events on stock markets using event study methodology. Kowalewski and Śpiewanowski [2020] study the impact of man-made and natural mining accidents on stocks of mining firms using event study methodology and multivariate regression analysis. Data was collected over a period of 33 years, between 1986 and 2019, during which a total of 64 disasters were identified. Stock returns, defined as  $\log r_t - \log r_{t-1}$ , is selected as the dependent variable and firm characteristics, number of casualties and media coverage derived from twitter are selected as the control variables for the multivariate regression analysis. It was found that naturally occurring events causing these accidents had a more profound impact on the stock returns of affected companies. Another important finding was the negative correlation of severity of the accident with the stock returns, that is higher magnitude of negative returns were observed with more number of casualties, and are accompanied by a reversal which is dependant on the magnitude of the event. The impact on returns of competitor companies was however

opposite. Returns of Competitors are impacted negatively only on the day of the event and with a reversal in the following days.

Shelor et al. [1990] assess the impact of Earthquake in 1989 on California based real estate firms. Stock returns of 19 companies headquartered in San Francisco and 44 outside San Francisco were selected for the study, and it was found for companies based in San Francisco negative returns were high with a statistical significance whereas for companies based outside of San Francisco, the negative returns were low and statistically insignificant. Shelor et al. [1992] extended their initial study and further found that insurance companies which were expected to see a negative reaction of returns to the natural disaster, were found to have a positive effect due to increase activity of purchasing of insurance.

As the same event under consideration can effect different stocks and indexes differently, the data selection for this research also considers indexes from stable and emerging markets, as well as individual firms across different sectors.

### **2.2.2 Political events and their impacts**

Bash and Alsaifi [2019] examine the effect on stock market of an unconventional event related to the disappearance of a public figure. All listed stocks in Saudi Stock Exchange were selected for this study and using mean equality tests on Average Abnormal Returns (AAR) and Cumulative Average Abnormal Returns (CAAR), calculated using the mean adjusted returns and market model returns, it was found that irrespective of a companies' sector, the returns showed a downtrend around the disappearance of Khashoggi. Further, by segregating the companies based on foreign ownership, it was concluded that the negative returns were driven mainly by local investors.

### **2.2.3 Terrorist attack events and their impacts**

Chen and Siems [2004] study the effect of 14 terrorist attacks dating back from 1915 on U.S. stock markets, including the September 2001 attacks on World Trade Centre. Using event study methodology, it was found that these events had a negative impact on the day of the event, however the returns on the subsequent days showed overall positive gains and indicated that U.S. stock markets have grown resilient to terrorist attacks and recover sooner. Karolyi and Martell [2006] studied the effects of 75 terrorism attacks in which specific firms were targets. Statistically significant results were found with overall  $-0.83\%$  stock price reaction. Further, a cross sectional study revealed that the impact of the attacks differed according to the firm's origin country as well as the country where the attack occurred and it was observed that attacks in wealthier and more democratic countries are associated with greater negative stock price reactions.

When studying the impact of an event across multiple firms, use of cross sectional analysis of the results shed light on insights that might otherwise be not observable. Hence, this research aims to organize the results from regression models in panel format and perform cross sectional analysis to derive results.

#### **2.2.4 Spread of Disease bases events and their impacts**

In the recent past, there have been several pandemic and epidemic, outbreak level events that affected to the stock markets and economies as a whole. The adverse impact of disease outbreaks is revealed in many studies. Some of the most notable ones include Avian Influenza in 1997, Severe Acute Respiratory Syndrome or SARS in 2003, Swine flu in 2009 to 2010, Ebola outbreak in 2014 to 2016 and Middle East Respiratory Syndrome or MERS outbreak in 2012.

During the occurrence of disease epidemics, much effort has been devoted to analyzing the presence of market overreaction, mainly in terms of abnormal returns. For instance, Chen et al. [2007] investigated the impact of the SARS epidemic on companies listed on Taiwanese Stock exchange. The impact was investigated using the Cumulative Abnormal Returns or CAR event study methodology across different estimation period windows and across companies from multiple sectors, namely Hotel, Automobile, Banking and Insurance, Food, Chemicals, Construction, Plastics, Textiles, Department Stores and Transportation. For both 10 and 20 day event window after the event, considerably negative cumulative abnormal returns were observed for almost all sectors, however only for the Hotel and foods industries was the negative impact statistically significant indicating that while all sectors were negatively impacted by SARS epidemic, Hotel and food sectors will be affected by any further such epidemics and should be prepared for it in the future.

Chen et al. [2009] further studied the SARS epidemic and its impacts on stock markets in Taiwan. For this research, stocks of companies belonging to airline, tourism and biotech industries along with GARCH or General Autoregressive conditional heteroskedasticity approach were selected for event study. It was discovered that the tourist and retail sectors in Taiwan had negative abnormal returns whereas biotech firms responded positively to the shock event of SARS, thus displaying that not all shock events impact the markets or firms negatively.

Ichev and Marinč [2018a] performed a similar research on the spread of H1N1 or Swine flu and its impact on stock returns of BRICs countries. This study used major indexes of each country as market proxy to understand the impact. It was observed that the not all countries responded the same way to the announcement of a pandemic.

Ichev and Marinč [2018b] provide evidence that corroborates the harmful consequences that the Ebola outbreak has had on American businesses with operations in West Africa. They explored the negative returns in U.S. stock market over a period of 2 years, between

2014 - 2016. The research used a panel regression approach to understand if the geographic proximity to an event related to Ebola virus had any significant impact on the returns. Using location of an event as a control variable, it was determined that the influence of the incident may be seen in each and every location of interest. It is larger and more statistically significant for the events that take place in the United States and the Western and Central Asia (WAC) region, as well as for the companies whose operations are only exposed to the United States, than it is for the events that take place in Europe, both for the companies whose operations are exposed to Europe and for the events themselves.

### **2.2.5 Covid 19 and its impacts**

Liu et al. [2020] explores the impact of Covid 19 on Chinese and Asian stock market, immediately after the announcement of the pandemic, using event study methodology. The study determined that both the Chinese and Asian stock markets had experienced significant declines, with the cumulative abnormal returns (CAR) remaining negative in all of the examined event window periods. The abnormal returns (AR) were calculated using an event study method in the 10 trading days following the outbreak. It also performed an analysis of the various industry index responses to the epidemic, from which it was determined that the manufacturing of pharmaceuticals, the provision of software and information technology services all had a positive CAR during the event window, whereas transportation, lodging and catering all had a negative CAR. These findings represented the expectations that investors had for the various sectors of the economy and the economy as a whole in light of the emergence of the infectious coronavirus.

Ramelli and Wagner [2020] provide more evidence that the United States stock market had an unfavorable response to the COVID-19 epidemic. In the research, they made use of market model to calculate the excess returns or abnormal returns during the event and used a panel regression model with firm characteristics such as Leverage, Cash/Assets and Foreign revenues as control variables.

Khan et al. [2020] studied the impact of Covid 19 on 16 countries, including U.S. India China amongst others, using Pooled OLS Panel Regression model. Stock returns series were regressed with weekly cases of Covid around the world for 6 weeks starting from February 17th, 2020. It was found that during the period of analysis, daily cases had a negative impact on stock returns in all markets.

## **2.3 Motivation**

On December 31, 2019, the first case of the Corona Virus, also known as Covid 19, was reported in Wuhan, China. This marked the beginning of the reporting of the spread of

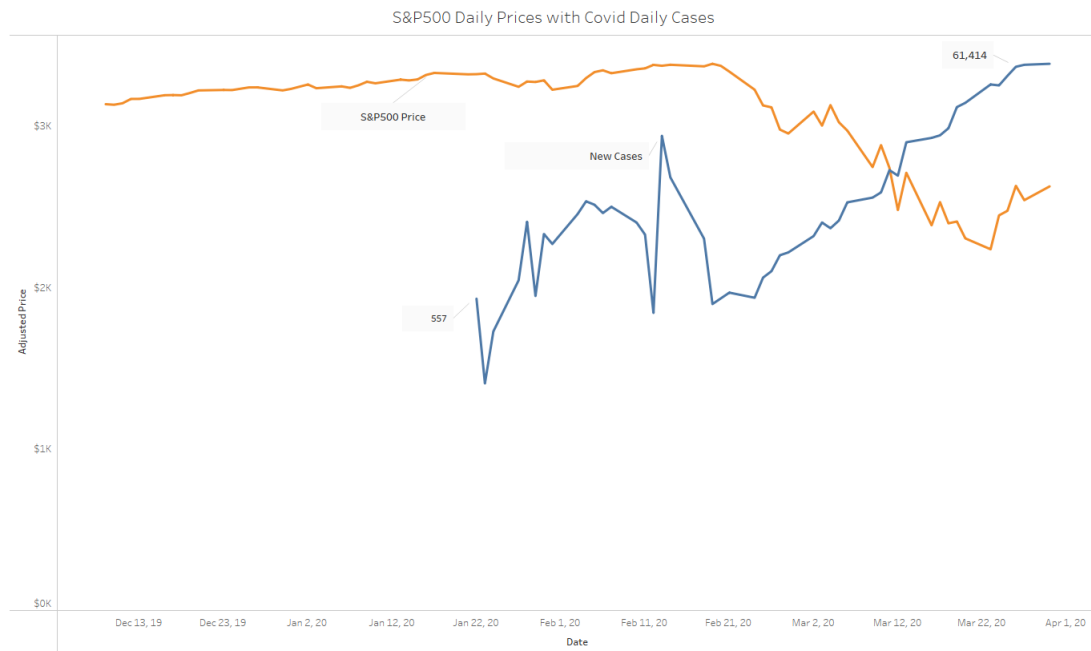


Figure 2.1: Market Response to Covid 19 spread: Daily Index Price of S&P500 with Globally recorded cases of Covid 19 from December 2019 to April 2020

the Corona Virus or Covid 19. The measures that were made to contain the virus were unsuccessful, and as a result, it soon spread throughout China and subsequently to other nations around the world. The World Health Organization, also known as WHO, declared a public health emergency of international concern on the 30th of January, 2019, and on the 11th of March, 2019, it proclaimed the illness to be a pandemic. By that time, the virus had already spread to practically all of the countries in the world, and there had been more than 120,000 instances of infection and more than 4,000 fatalities documented. Countries were forced to implement strict regulations, such as putting the entire nation under lockdown, compelling inhabitants to remain inside their homes, and allowing them to leave their homes only in extraordinary circumstances. Companies all across the world incurred losses as a direct result of the implementation of these strict regulations. Companies that were able to adapt by allowing employees to work from home continued operations as best they could, whilst other businesses were forced to shut down permanently, resulting in the loss of employment for a portion of the population. As a direct consequence of this, the economies of virtually all nations were severely disrupted.

When it was discovered that overall economies all over the world were being considerably influenced, it was also observed that financial markets were being impacted in the same way. As the information about Covid 19 circulated, the markets responded in an unexpected manner and declined by nearly 30 percent.

Daily price of Standard and Poor's 500 index, a US market index which tracks 500 publicly traded domestic companies, saw a decline from \$3,000+ to \$2,000 with the initial spike

recorded in the daily cases (**Figure (2.1)**).

According to the efficient market hypothesis Fama [1970], all the information required in order to determine the intrinsic value of a financial asset is contained in the price of the asset, and only new information released causes the price to fluctuate before the market slowly absorbs the new information and stabilizes by buyers and sellers discovering the new price. To understand this, there are different school of thoughts to map the effect of such events, such as Fundamental analysis which is determining an asset's intrinsic value by studying the financial statements of a company, including their income and expenditure. Another type of analysis is the Technical analysis where flow of information into the market about an asset, along with the demand of the asset is taken into consideration to determine the intrinsic value of the asset. The last type of analysis used by analysts is the behaviour analysis or behavioural finance, that is explaining the price movements in market through the study of behaviour of investors and traders, which is influenced by their perception about a company. And during Covid 19, there was mass panic observed in the first month of Covid 19 being declared as a pandemic, and what followed was an overall mass sell off in the market. Looking at **Figure (2.1)** and the fluctuations in price of the market, to say that flow of information during the pandemic was disrupted and the markets were not able to assimilate the effect of it completely would not be wrong. Therefore, the thesis explores the use of Covid 19 daily cases as a proxy for news related to it and study it's impact on the stock markets. Behavioural analysis is selected as the basis of this research to study the impact of shock events on the markets.

While there have been a few studies to understand the impact of Covid 19, they have all been short term upto 4 months after the start of Covid 19, with majorly firm statistics and in one case, volume of news of Covid 19 on Twitter, but do not take into consideration the daily cases as a control variable. Therefore, this research uses the event study methodology to understand the impact of Covid 19 by taking the event window from the start of Covid 19 cases being recorded, which is January 22<sup>nd</sup> 2020, to December 31<sup>st</sup> 2021, using log difference of daily Covid 19 cases as recorded by the John Hopkins University (Dong et al. [2020]).

# Chapter 3 – Methodology

## 3.1 Introduction

This chapter provides an insight and detailed explanation of the data pipeline, including the data source, transformations and aggregations, built to perform the analysis, methods used for data analysis and their relevance to this research. It is divided into the following parts:

- Data Pipeline
- Statistical Time Series Analysis
- Tools used

Each section further contains the information about the steps followed in each section and detailed explanation of the methods used in conducting the research. Implementation of the case study is discussed in the next chapter, that is Chapter 4 -Case Study and Results.

## 3.2 Data Pipeline

This section consists of the steps followed in building the entire pipeline including data extraction and any pre-processing and transformations applied. **Figure 3.1** shows the model architecture, giving an overview of the data flow and methodologies used in the research. Using an input list of stock names or ticker symbol as on Yahoo finance, time series proxy data of event variable and period of analysis, the script extracts daily prices using APIs for the given list of symbols, transforms the price series and merges it with time series proxy data for shock event. Next, descriptive statistics and stylized facts are obtained for the daily price series, and along with that Auto-regression models are built, to determine the impact of shock event on daily price time series.

# Model Architecture

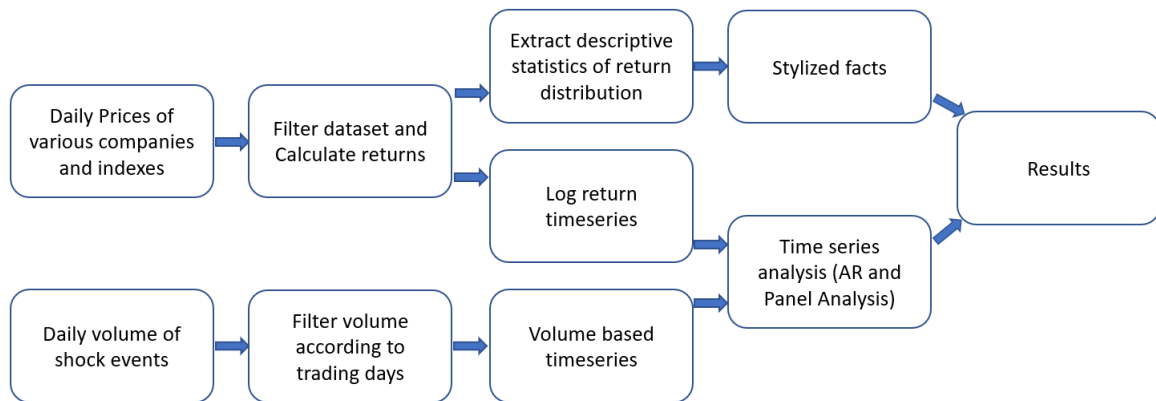


Figure 3.1: Model Architecture

## 3.2.1 Data Extraction

Data extraction is the process of collecting or obtaining the data from the source using various methods such as data scraping, data crawling, APIs etc. This section covers the sources from which financial time series data and COVID 19 time series data is extracted.

### Stock Price Time Series Data

Financial time series Data was obtained using *quantmod* package in R programming language. The package allows users to extract historical stock price data from multiple sources with the optional input of time range and frequency. Yahoo finance was chosen as the source within *quantmod* package, which is a popular and trusted source for stock price data.

### COVID 19 Time Series Data

Daily new cases of COVID 19, used as a proxy for sentiment introduced by the pandemic, have been collected by the Center for Systems Science and Engineering (CSSE) at the John Hopkins University, which is further supported by the ESRI Living Atlas team and the John Hopkins University Applied Physics Lab Dong et al. [2020]. The data set is available for public use, is collected from multiple sources around the world and collects various data points by country and date including daily and cumulative new cases and deaths. *Our World in Data* further cleans and combines this data set with other data points such as Testing, Hospitalization, Vaccinations and Mortality rates Hannah Ritchie and Roser [2020]. Due to the transformations applied by *Our World in Data* and further enriching of the data set by adding more dimensions, it was chosen as the source for this research.



### 3.2.2 Data Pre-processing

Data Pre-processing is the step where raw data is modified to make into a system readable format. As the data for Financial time series was directly imported into R software environment and COVID 19 cases data was exported from *Our World in Data* as csv, which was also imported directly into R software environment, there were no data pre-processing steps involved.

### 3.2.3 Data Transformation

Data Transformation is the process of cleaning, formatting, filtering and merging the data, which is then further used by statistical models. This section covers the steps applied to both financial and COVID 19 cases data set, in individual sections.

#### Stock Price Time Series Data

It was found that previous day lags of stock prices were highly correlated, that is the stock price at a given time was heavily affected by the previous days' prices, and hence would not allow for the models to be correct (Show the correlation of lags). Therefore, a more common method is to use the log values of Adjusted closing price Ultsch [2008], which is defined as:

$$r_t = \log_{10} \frac{AdjPrice_t}{AdjPrice_{t-1}} \quad (1)$$

where  $r_t$  is the Return at time t,  $AdjPrice_t$  is the Adjusted closing price at time t and  $AdjPrice_{t-1}$  is the Adjusted closing price at time t-1. Transforming the Adjusted Closing Price as a time series of returns helps by making the series more stationary. The Return time series is used as the dependent variable as there is no correlation between lagged values of Return.

Further, z-score values of log difference are calculated using the below formula:

$$r_{t\_z-score} = \frac{r_t - \mu_r}{\sigma_r} \quad (2)$$

where  $\mu$  is the mean and  $\sigma$  is the standard deviation.

#### COVID 19 Time Series Data

It was observed that COVID daily cases during the start of the pandemic were on the scale of hundred to thousand whereas towards the Due to the large variance in the scale of values pertaining to daily cases of COVID, log values of daily cases was derived. For days with no reporting of cases or 0 cases reported, log value was taken as 0. Further, the log values or daily cases are transformed into z score values with the same formula as equation 2.

## Data Aggregation

The financial data time series is a five day time series with stock prices available for all weekdays except for holidays and COVID daily cases are available as a 7 day time series, that is cases are reported everyday. Both the time series are merged on the basis of intersection of dates available, for stock prices as well as COVID daily cases.

## 3.3 Statistical Time Series Analysis

The research progresses by making use of the data collected via the pipeline described above for extracting the stylized facts of financial time series data using descriptive statistics of the data and building auto-regression models to analyze the impact of sentiment contained in COVID 19 daily cases volume on returns. For stylized facts, return time series of daily stock prices is considered and for Auto regression models, return time series is taken as the dependent variable and Covid 19 daily cases as well as log difference of daily cases along with 5 lags of dependent variable are taken as the independent variable.

### 3.3.1 Stylized facts of Financial Time Series Data

Stylized facts are general properties that can be expected to be found in any set of returns time series. These are pervasive across time and financial instruments and are used when comparing different financial assets Taylor [2005]. Three main stylized facts are as follows:

1. Distribution of returns is not normal.
2. There is almost no autocorrelation between returns for different days.
3. The correlation between the magnitudes of returns on nearby days are positive and statistically significant.

For the purpose of this research, first two stylized facts are considered. Using the following set of descriptive statistics of a return time series data, empirical findings around stylized facts are presented:

1. Mean( $\mu$ ) - It is defined as the average value of a distribution and is given by  $\frac{1}{n} \sum_{i=1}^n x_i$ .
2. Standard deviation( $\sigma$ ) - It is defined the variation in the distribution and is given by  $\frac{1}{n-1} \sum_{i=1}^n (x_i - \mu_x)$ .
3. Skewness (b) - It is defined as the asymmetry a distribution has from a normal distribution and is given by  $\frac{1}{n-1} \sum_{i=1}^n \frac{(x_i - \mu_x)^3}{\sigma^3}$ . For a normal distribution, this should be 0. A Negative skewness indicates longer left tail in the distribution whereas a positive value indicate longer right hand side tail.

4. Kurtosis (k) - It is defined as the relative flatness of the tails of the distribution with respect to the centre of the distribution and is given by  $\frac{1}{n-1} \sum_{i=1}^n \frac{(x_i - \mu_x)^4}{\sigma^4}$ . For normal distribution, this should be 3. Distributions that have kurtosis higher than 3 have longer and skinnier tails, and are defined as Leptokurtic distributions and distributions that have kurtosis lower than 3 have shorter and fatter tails, and are defined as Platykurtic distributions.

### 3.3.2 Linear Regression

To understand Auto-regression and Vector Auto-regression models, it is important to first understand a Linear regression model. Linear regression is the approach to model linear relationship between a dependant scalar variable and an independent scalar variable. When more than one independent variables are used to map the relationship, it is defined as multiple linear regression. A generalized linear equation takes the following form:

$$Y = \alpha X + const. + \epsilon \quad (3)$$

where Y is the dependent variable, X is the independent variable, const is the average change in dependent variable,  $\epsilon$  is the error term or residuals and  $\alpha$  is the regression coefficient of X. The coefficients are calculated using Ordinary Least squares or OLS. A linear regression model works on the following assumptions:

1. Linear Relationship - The relation between dependent and independent variable should be linear.
2. Multivariate Normality - For a particular value of X, Y is distributed normally.
3. Homoscedasticity - Variance in residuals is the same for particular value of X.
4. No Multicollinearity - Independent variables are not correlated with each other.
5. No Autocorrelation - Residuals of the dependent variable do not have a linear relationship.

If any of the above assumptions are violated, the results from the model are considered to be not accurate. A Linear regression model is evaluated using the  $R^2$  value, which tells about the variance in the dependent variable explained by the model. The value ranges from 0 to 1 and the closer the value is to 1, the better the model.

### 3.3.3 Auto Regression

An Auto-regression model is time-series model which maps the relation of the dependent variable with previous time lagged values of itself, along with the stochastic or random noise

term. Auto-regression model equation takes the following form :

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \beta_3 Y_{t-3} + \epsilon \quad (4)$$

where  $\alpha$  is the regression constant ,  $\beta_n$  is a vector of  $n \times 1$  values corresponding to the  $n$  Lag values of  $Y$  represented by  $Y_n$  and  $\epsilon$  is the error term.

For this research, three Auto regression models are used as control variables to determine the impact of Covid 19, defined as follows:

$$r_t = \alpha_0 + \beta_1 r_{t-1} + \beta_2 r_{t-2} + \beta_3 r_{t-3} + \beta_4 r_{t-4} + \beta_5 r_{t-5} + \epsilon \quad (5)$$

where  $r_t$  is the return value on current day,  $\alpha$  is the regression coefficient or the mean value of returns,  $\beta$  are the coefficients of the 5 day lags and  $\epsilon$  is the error term.

$$r_t = \alpha_0 + \beta_1 r_{t-1} + \beta_2 r_{t-2} + \beta_3 r_{t-3} + \beta_4 r_{t-4} + \beta_5 r_{t-5} + \gamma C19Cases_{abs} + \epsilon \quad (6)$$

where in addition to eq 5,  $C19Cases_{abs}$  represent the daily cases of Covid 19 cases and  $\gamma$  is the regression coefficient of daily cases.

$$r_t = \alpha_0 + \beta_1 r_{t-1} + \beta_2 r_{t-2} + \beta_3 r_{t-3} + \beta_4 r_{t-4} + \beta_5 r_{t-5} + \gamma C19Cases_{Indiff} + \epsilon \quad (7)$$

where in addition to eq 5,  $C19Cases_{Indiff}$  represent the log difference of daily cases of Covid 19 cases and  $\gamma$  is the regression coefficient of log difference of daily cases.

### A note on Heteroskedasticity

The term "heteroskedasticity" is used to describe circumstances in which the standard deviation of the residuals varies unequally over a range of measured values. In the process of doing a regression analysis, heteroskedasticity causes the residuals to scatter in an uneven manner (also known as the error term).

When looking at a plot of the residuals, if the form looks like a fan or a cone, this suggests that heteroskedasticity is present. Because regressions using ordinary least squares (OLS) presume that the residuals are obtained from a population with constant variance, heteroskedasticity is considered as a difficulty in the field of statistics.

If there is unequal dispersion of residuals, this indicates that the population employed in the regression includes unequal variance, and as a result, the conclusions of the study may be erroneous.

Residuals obtained from a market model of stock returns, that is return regressed on previous five day lags, have been found to be heteroskedastic in nature (Morgan [1976]), that is the residuals of returns vary with time. In order to deal with heteroskedastic nature of these residuals, Heteroskedastic-consistent standard robust errors are used (Newey and West [1987]). The following formula is used to calculate the standard robust errors:

$$HC_1 = \frac{n}{n-k} \hat{\mu}_i^2 \quad (8)$$

where  $n$  is the number of observations,  $k$  is the number of coefficients and  $\hat{\mu}_i^2$  are the squared residuals.

### 3.3.4 Panel Data Study

In the fields of medicine, social science, and biology, an observational study known as a cross-sectional study (also known as a cross-sectional analysis, transverse study, and prevalence study) is a type of study that analyzes data collected from a population or a representative subset of the population at a particular point in time. This type of data is referred to as cross-sectional data.

In the field of economics, cross-sectional studies almost always involve the application of cross-sectional regression. This method is used to determine whether or not there is a causal effect of one independent variable upon a dependent variable of interest at a particular point in time, as well as the magnitude of any such effect. They are distinct from time series analysis, which follows the pattern of behavior of one or more economic aggregates over the course of a specified period of time.

Results obtained from Auto regression model are organised according to the sectors identified for this research and analyzed cross section-ally to identify patterns and causal relationship between sectors.

## 3.4 Tools and Software Used

### 3.4.1 Tableau

Tableau is an application for data visualization and business intelligence that gives users the ability to generate ad hoc charts and dashboards in order to better comprehend and analyze data sets. The user is provided with the opportunity to input data from a diverse range of sources and file types, and the system is also equipped with the capability to combine data from a number of different data sets. It includes regularly used forms of charts that may be used as templates to make the generation of visualizations quick and easy, and it provides a

drag-and-drop interface that can be used to pick the information that will be shown. Tableau also delivers interactive graphics, which enable users to explore data by employing a wide array of graphical representations in a number of formats.

### **3.4.2 R Programming Environment**

R is a computer language for statistical computing and graphics that may be used to clean, analyze, and graph your data. It was developed by the R Foundation for Statistical Computing and Graphics. Here you will find other resources pertaining to R. Utilizing the R packages that are available for download allows users to access pre-built functions that may be used for a wide variety of statistical analyses and tests. Throughout the whole of the process of developing the pipeline for this research, R studio was employed in various capacities. This includes the processes of data extraction, transformation, and aggregation, in addition to the statistical analysis that was carried out to evaluate the impact of the change. The script was created in such a manner that it may be modified to function with a variety of indices in addition to specific firms. This was done intentionally.

# Chapter 4 – Case Study and Results

The aim of this chapter is to formalize the case study to which the described methodology is applied, discuss the results obtained from the applied methodology for the selected use case. The section is further divided into the following sections:

1. Case Study
2. Descriptive Statistics and Stylized Facts
3. Statistical Analysis

The Case study section elaborates on the data exploration findings as well as the specific use case on which this research is focused on, Descriptive Statistics and Stylized facts section finds out if the return series conform to the Stylized facts of returns as found by Taylor [2005] and finally, the Statistical analysis section discusses on the evaluation of event and its inference.

## 4.1 Case Study

Hundreds of thousands new cases still being identified across the world as a result of the pandemic, however with death rate not as significant, it can be said that Covid 19 along with its mutation is here to stay. There seems to be no permanent solution to stop the spread of virus. However, whether it is still deemed as deadly and contagious by the world is debatable. With restrictions imposed by the governments almost lifted, the world opening back up and returning to its normal self, it would be interesting to see if the financial markets responded in the same way. Data exploration techniques are used to study this relationship.

### 4.1.1 Data Selection

The research focuses on computational analysis of a shock event Covid 19 pandemic on stock markets and therefore, daily stock market returns are considered as the dependent variable and daily Covid 19 cases are considered as the independent variable. As it has been observed

that a particular event can have varying impact on markets, the dependent variable or the market proxy is further divided into indexes and firms. Indexes are further classified as stable and emerging markets. Data Selection is based on selecting indexes and key companies that may or may not have been effected. Further, the time period for the data set is considered from 22<sup>nd</sup> January, 2020 to 31<sup>st</sup> December, 2021 as the starting date marks the availability of data for Covid 19 cases and the end of 2021 marked the end of 2<sup>nd</sup> wave of Covid 19. In the next three sections, reasoning behind the selection of indexes and firms has been discussed.

### **Index - Stable Market**

A stable or a developed market can be defined as one that is most developed in terms of its economy and capital markets, with high level of regulation and oversight and good liquidity in its debt and equity. The country has high income, which also includes openness to foreign ownership, ease of capital movement, and efficiency of market institutions.

As a proxy for stable markets, Standard & Poor's 500 or S&P 500 and Dow Jones Industrial Average or DJIA indexes are selected. The Standard & Poor's 500 Index, known simply as the *S&P 500 Index*, is a weighted index that tracks the performance of the 500 most important publicly listed firms in the United States by market capitalization. Due to the fact that the index takes into account a variety of other factors, the list of the top 500 corporations in terms of market capitalization in the United States is not exhaustive. A committee is responsible for selecting the components that make up the SP 500 index. Market capitalization, liquidity, domicile, public float, Global Industry Classification Standard and representation of the industries in the economy of the United States, financial viability, length of time publicly traded, and stock exchange are the eight primary criteria that are evaluated by the committee when determining whether or not a new addition is eligible for consideration.

The Dow Jones Industrial Average, known as the DJIA, is a stock market index that gauges the performance of 30 of the most recognizable companies listed on U.S. stock exchanges. As opposed to S&P500 that is weighted by market capitalization, this index is price-weighted.

Stable markets, such as *S&P 500* and DJIA consisting of U.S. based companies who have footprints around the world, have been observed to be affected by news introduced sentiment from across the globe, and therefore, daily Covid 19 cases as a shock variable are considered at the World level, that is cases recorded across all countries.

### **Index - Emerging Market**

Emerging market can be defined as one which have limited aspects of a developed market and does not meet all the standards of a developed market. These markets are characterized by low income and high growth economies. As these markets develop, they become more integrated with developed markets, with increased liquidity, trading volumes and foreign direct



investments.

India, amongst other countries such as China, Brazil, Mexico, Russia etc, is considered an emerging market. Therefore, daily price returns of Bombay Stock exchange or BSE is considered as a proxy for emerging markets. The Bombay Stock Exchange Sensitive Index (also known as the *S&P* Bombay Stock Exchange Sensitive Index or simply SENSEX) is a free-float market-weighted stock market index that consists of 30 well-established and financially sound companies that are listed on the Bombay Stock Exchange. The 30 member businesses, which include some of the largest and most regularly traded equities, are representative of a variety of industrial sectors in the Indian economy. They are also among the most actively traded stocks. It is widely recognized as the index that best represents the local stock markets in India.

Emerging markets, have little effect of sentiment and news from across the world and are more affected by sentiment from within the country and therefore, for emerging markets, daily cases of Covid 19 are filtered by the country.

### Individual Firms

Along with indexes, it has been observed that major events have impact at index level as well as firm level. Therefore, 14 firms across 4 different sectors, namely Banking, Pharmaceutical, Information Technology and Automotive, have been shortlisted for the research. The firms selected across different sectors are exemplaries of their respective sector and form a representative sample of the population of the sector. **Figure 4.1** shows an overview of the different sectors and how the composition of selected firms overlap with different indexes. All of the IT and Banking sectors firms are such that are traded in both S&P500 and BSE, from Pharmaceutical and Automotive, only 1 firm is traded across both the markets and the rest are only traded on S&P 500 The 4 different sectors selected are as follows:

1. **Automotive** - The sector comprises of companies involved in manufacturing and sale of automobiles and can be considered as a representation of consumer spending habits, which is considered to have changed since Covid 19. Along with that, it can be characterized by considerable delays in production due to global lockdown and supply chain disruption Pujawan and Bah [2022]. For these reasons, the sector is thought of as an interesting one for this study was included. 5 firms namely, Tata Motors (TTM), Toyota Motors (TM), Ford Motors (F), Honda Motors (HM) and General Motors (GM) were selected from the Automobile sector.
2. **Information Technology** - The information technology (IT) sector includes companies that produce software, hardware or semiconductor equipment, and companies that provide internet or related services. During Covid 19, IT companies adapted to the lockdown with introduction of work from home which involved massive overhauls to

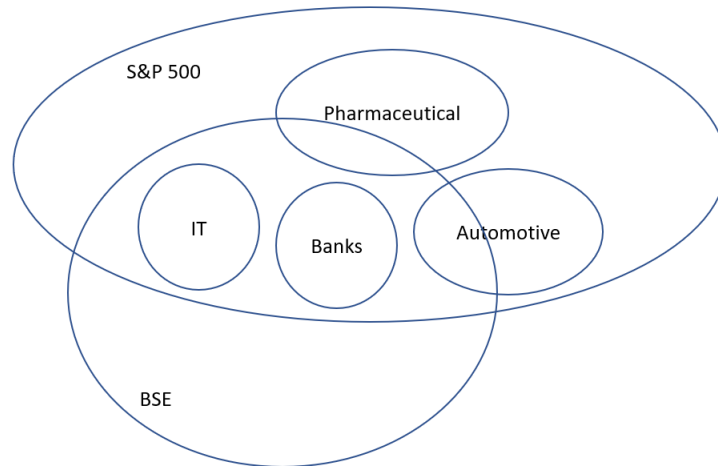


Figure 4.1: Composition of selected Individuals firms with Indexes

existing infrastructure. With the sudden increase of load on resources and growing concern around pandemic, it would be interesting to see how the IT sector incorporated the sentiment introduced by the pandemic. Two firms, namely Infosys (INFY) and Wipro (WIT) were selected from the IT industry.

3. **Banking** - Banking sector comprises of all licensed financial institutions such as banks which can provide lending and investments as well as financial holding institutions. This sector is considered as the backbone of the economy and is put to test with sudden economic slowdown. Along with that, increase in daily cases and unemployment going up with extended lockdowns, default rates on loans is expected to rise till the time a solution is found. For these reasons, the banking sector was selected for this research. Three banks, namely Axis Bank (AXS), ICICI Bank (IBN) and HDFC Bank (HDB) were selected from the Banking Industry.
4. **Pharmaceutical** - The pharmaceutical sector comprises of companies, according to Wikipedia, that "discover, develop, produce, and markets drugs or pharmaceutical drugs for use as medications to be administered to patients, with the aim to cure them, vaccinate them, or alleviate symptoms." This sector has a significant role to play in alleviating the negative sentiment introduced in the market due to Covid 19 with the trials, approval and production of vaccines and was therefore selected for this research. Four firms, namely AstraZeneca (AZN), Moderna (MRNA), Pfizer (PFE) and Reddy's Laboratories (RDY) were selected for this research.

#### 4.1.2 Exploratory Data Analysis

When observing the movement of *S&P500* index's daily prices, a proxy for stable markets, along with Covid 19 daily cases, deaths and vaccinations throughout the world, it is observed

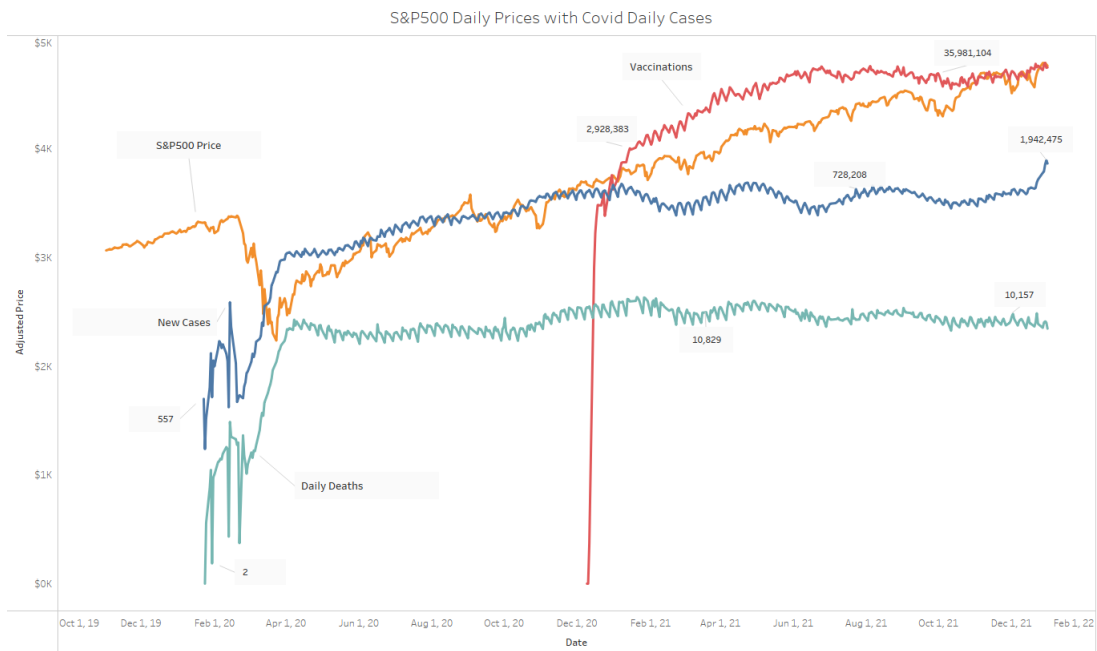


Figure 4.2: S&P500 daily prices along with daily Covid 19 cases, deaths and Vaccinations

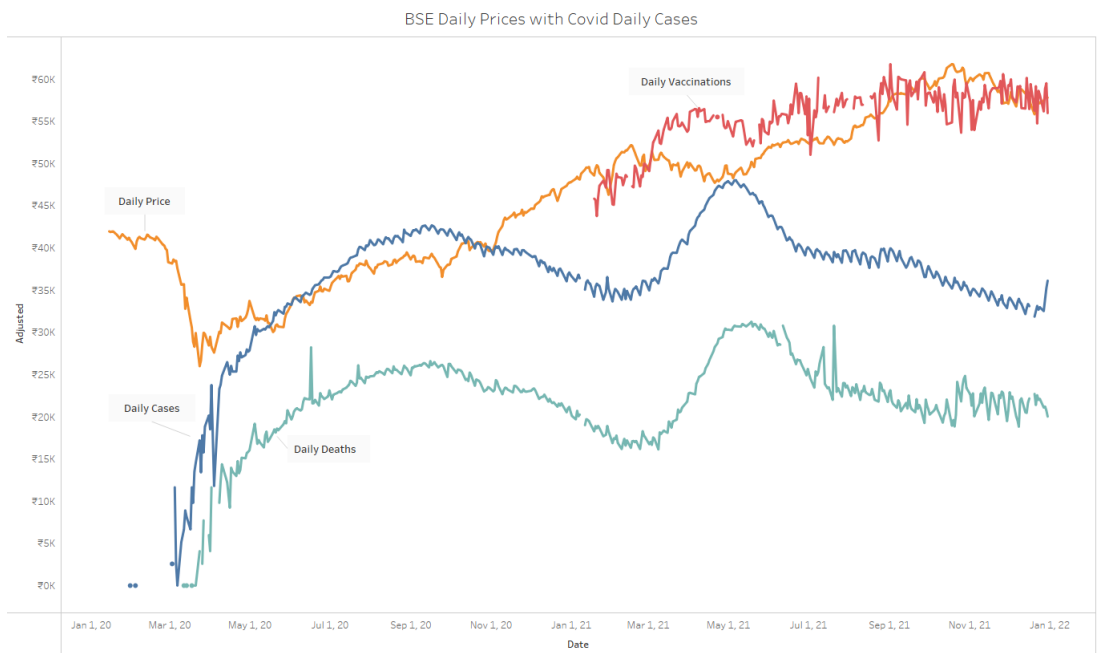


Figure 4.3: BSE daily prices along with daily Covid 19 cases, deaths and Vaccinations

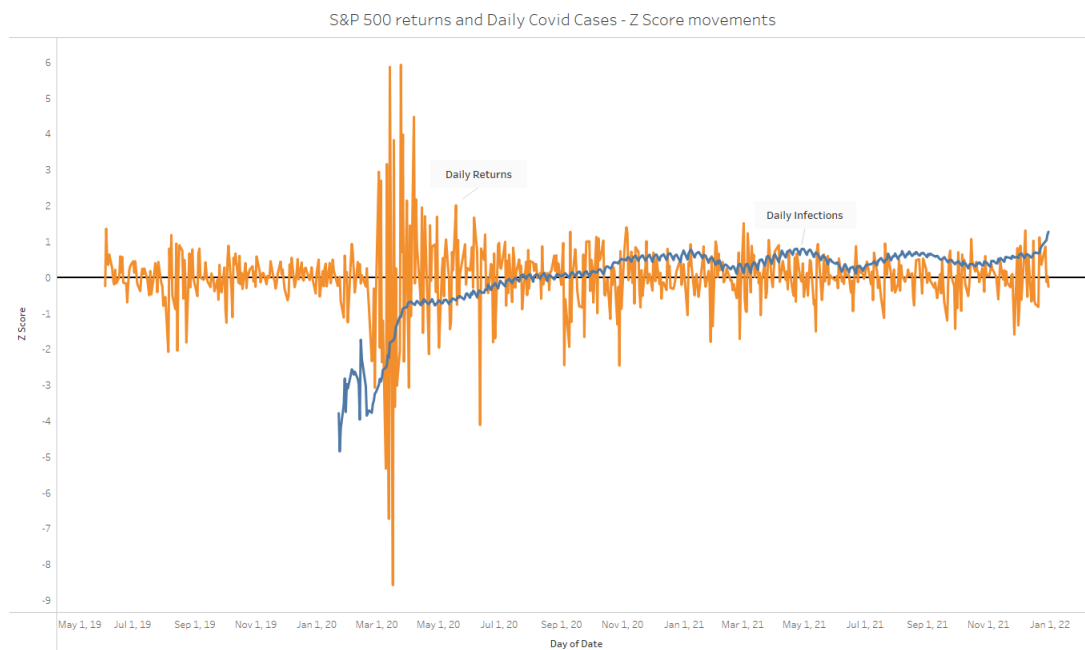


Figure 4.4: Z Score fluctuations of *S&P500* returns and Covid 19 daily infections

that during the start of the pandemic, when daily cases recorded were significantly lower than during the second wave, there was a sharp decline in prices between February 20<sup>th</sup> 2020 and March 11<sup>th</sup> 2020 (**Figure 4.2**). The index lost approximately 33 percent in less than a month. However, ever since the initial drop, the index seems to be on steady climb barring the occasional drops and visually, there were no significant response to the rise in deaths or vaccinations throughout the world. Same phenomena is witnessed in Bombay Stock Exchange daily prices (**Figure 4.3**), however, the daily numbers for Covid 19 are localized, that is only related to the origin country of stock market which is India, as Bombay Stock exchange is considered as a proxy for emerging markets which respond more to localized events than global events. Almost the same effect can be seen for BSE as well where at the start of the pandemic, the market fell from 40,000 to 25,000 rupees in the same time frame as *S&P500*

Fluctuation in Z Score values of *S&P500* daily returns and Covid 19 global daily infections between 1<sup>st</sup> June, 2019 and 31<sup>st</sup> December, 2021 is studied (**Figure 4.4**). Z Score value can be defined as how far or how many standard deviations away a value in the series is from its mean value. To understand the chart, June 2019 to December 2019 is considered as the pre-event window and January 2020 to December 2021 is considered as the event window. When analysing the pre-event window, it can be observed that returns do not fluctuate considerably from the mean value and are concentrated within the 2 and -2 standard deviations away from the mean. However, with the rise in Covid cases from January 2020, the returns started fluctuating very far from the mean, between 6 and -8 standard deviations away. This phenomena continues till July 2020 before the returns start to settle back in their usual pattern.

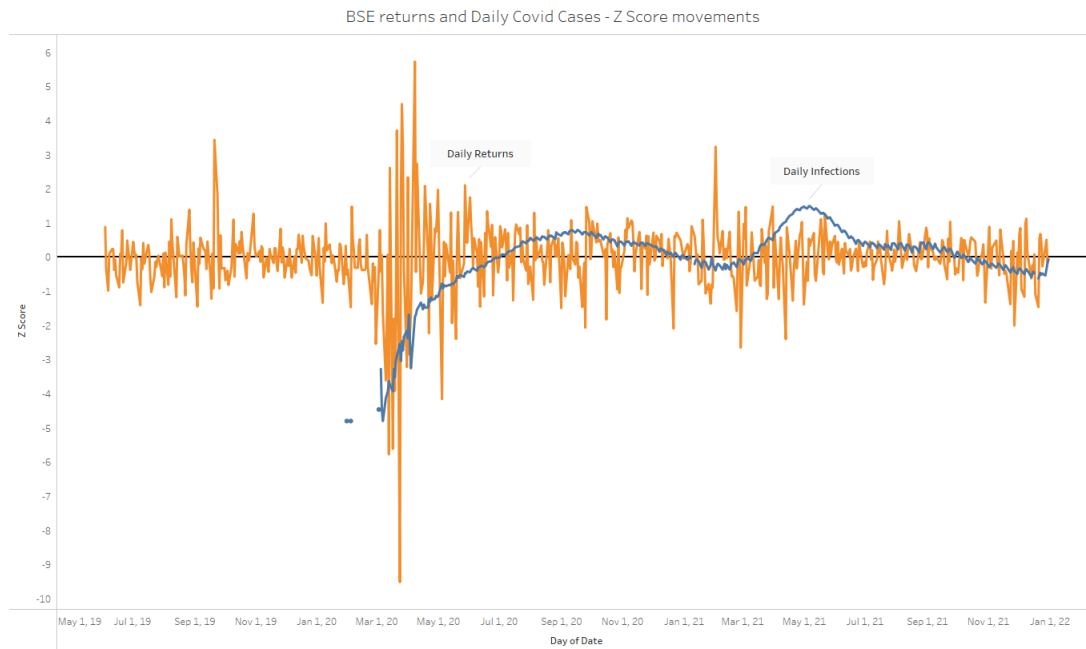


Figure 4.5: Z Score fluctuations of BSE returns and Covid 19 daily infections

Z score fluctuations of stock returns of BSE and Covid 19 daily infections are also observed, with the change that rather than global daily infections, Z score of localized infections or daily cases only in India are considered (**Figure 4.5**). Similar to what is observed with stable markets or *S&P500* daily returns, daily returns for BSE in the pre event window are also concentrated between 2 and -2 standard deviations away from the mean, and the rise in Covid 19 cases triggers an effect due to which BSE returns fluctuate significantly more than in the pre event window, with returns being 6 and almost -10 standard deviations away from the mean, and reverting back to their pre event window state from July 2020, around the same time as *S&P500*.

Financial markets are characterized by mean reversion, that is for every uptick in returns, a downtick in returns is expected. However, from the previous analysis, it can be seen that both *S&P500* and BSE returns did not conform to the mean reversion for almost 5 months since the start of pandemic. And from July 2020, both *S&P500* and BSE returned to their original state of mean reversion. What is interesting to note is that by the time daily infections reached their average cases over two years, the markets had started to exhibit mean reversion, indicating that all the information regarding Covid 19 was already absorbed in the returns, and there was no effect of further news around the pandemic such as vaccination role out throughout the world or more deadly and contagious mutations of the virus being discovered.

The returns are analyzed further by breaking the event window down further into 3 months window and mean and correlation are analyzed. **Figure 4.6a** to **Figure 4.10a** present the change in mean of return from June 2019 to December 2021, where the means are calculated for the pre-event window of 6 months from June to December 2019 together, and the event

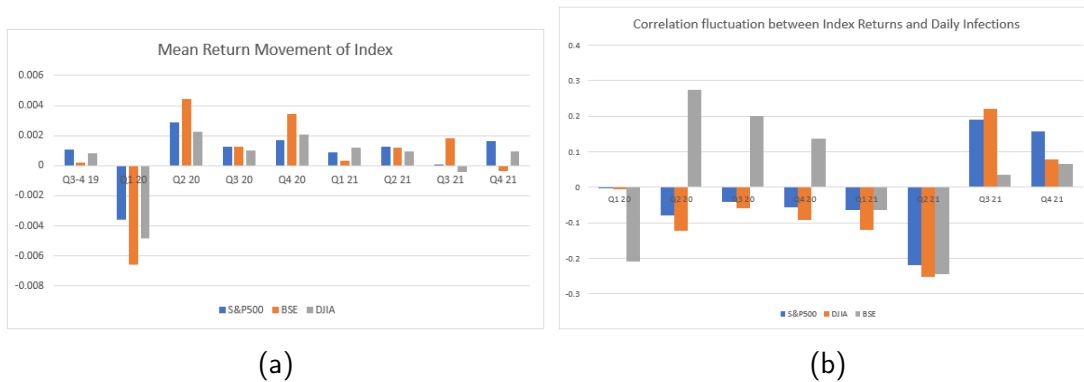


Figure 4.6: Index Exploratory Analysis: 4.6a shows the change in mean of Index returns over two and half years, with pre event window from June 2019 to December 2019 and event window between January 2020 to December 2021 split quarterly. 4.6b shows the correlation change between Index returns and Covid 19 daily infections over the course of event window, split quarterly.

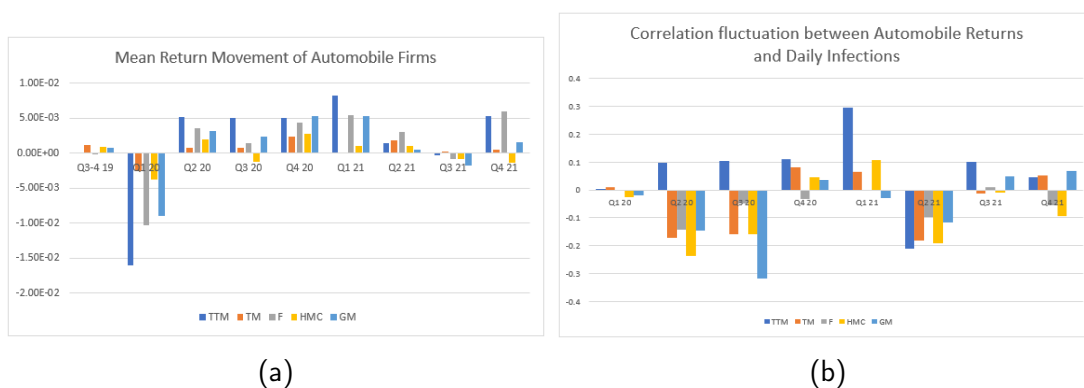
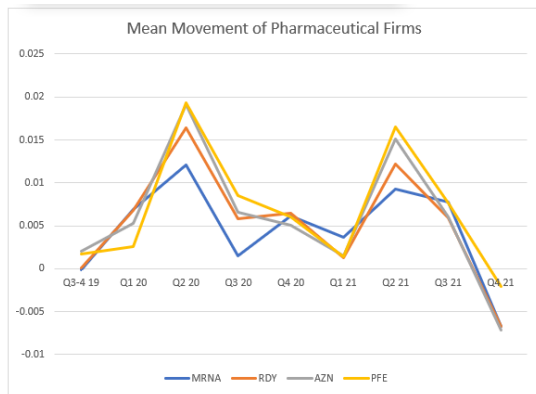


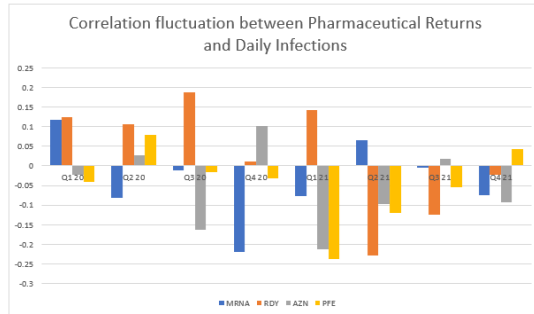
Figure 4.7: Automobile Sector Exploratory Analysis: 4.7a shows the change in mean of Automobile Sector returns over two and half years, with pre event window from June 2019 to December 2019 and event window between January 2020 to December 2021 split quarterly. 4.7b shows the correlation change between Automobile Sector returns and Covid 19 daily infections over the course of event window, split quarterly.

window is broken down in quarter starting from January 2020 to December 2021. The charts represent Index, Automobile, Pharmaceutical, Banking and IT sector in that order. In similar fashion, **Figure 4.6b** to **Figure 4.10b** present the change in correlation of returns and daily infection during the event window segregated into quarters starting from January 2020 to December 2021. The charts represent Index, Automobile, Pharmaceutical, Banking and IT sector in that order.

Mean Return for all three indexes were approximately 0 during the last two quarters of 2019 and with the advent of Covid 19, there was a significant negative change in the means for the first three months. However, the second quarter saw another swing in the mean of returns with all three indexes now having a +ve mean and over the next 6 quarters, gradually reverting to the average returns during the pre event window (**Figure 4.6a**). When understanding correlation movements, one can see that *S&P500* and *BSE* are very similarly correlated to

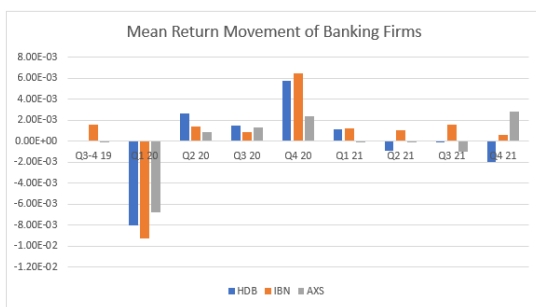


(a)

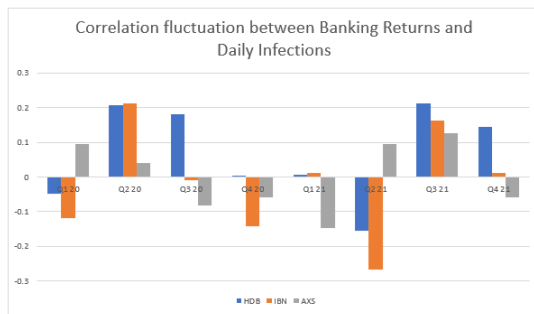


(b)

Figure 4.8: Pharmaceuticals Sector Exploratory Analysis: 4.8a shows the change in mean of Pharmaceutical sector returns over two and half years, with pre event window from June 2019 to December 2019 and event window between January 2020 to December 2021 split quarterly. 4.8b shows the correlation change between Pharmaceutical sector returns and Covid 19 daily infections over the course of event window, split quarterly.



(a)



(b)

Figure 4.9: Banking Sector Exploratory Analysis: 4.9a shows the change in mean of Banking sector returns over two and half years, with pre event window from June 2019 to December 2019 and event window between January 2020 to December 2021 split quarterly. 4.9b shows the correlation change between Banking sector returns and Covid 19 daily infections over the course of event window, split quarterly.

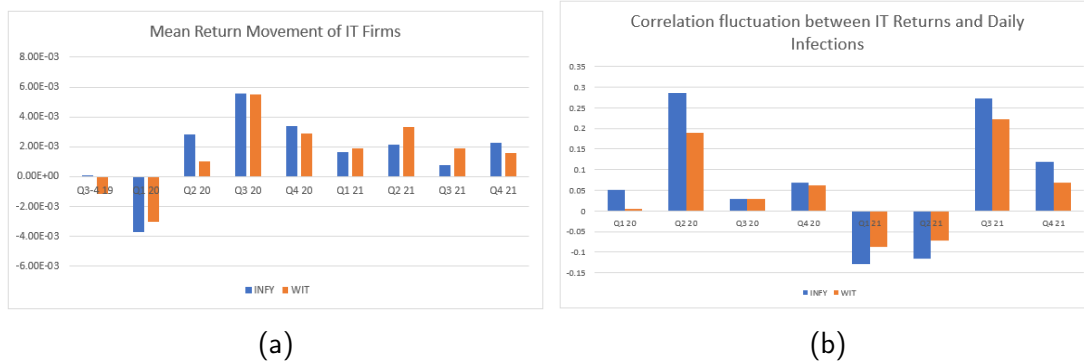


Figure 4.10: IT sector Exploratory Analysis: 4.10a shows the change in mean of IT sector returns over two and half years, with pre event window from June 2019 to December 2019 and event window between January 2020 to December 2021 split quarterly. 4.10b shows the correlation change between IT sector returns and Covid 19 daily infections over the course of event window, split quarterly.

the daily infections, with almost no correlation in the first quarter and then being negatively correlated with daily infections, that is daily returns were more positive with decrease in number of cases. However, Dow Jones Industrial Average started with negative correlation and from quarter two in 2020, was positively associated with increase in daily infections, with a gradual decline in the magnitude of positive association. From the beginning of 2021, all three indexes started to exhibit a similar response, with the first half having negative correlation and second half showing positive correlation (**Figure 4.6b**).

At firm level, in the last two quarters of 2019, the mean of returns was slightly positive but approximately 0, and in the first quarter of 2020, the mean dipped significantly below 0 for all 5 automobile firms. In quarter two of 2020, it jumped back to above 0 and staying in the positive region till second quarter of 2021, after which the average return was again almost 0 and then rising again in the last quarter of 2021. All 5 firms display a similar change in means throughout (**Figure 4.7a**). Change in correlation however follows a different trend. 4 out of the 5 firms have an initial negative response to daily infections, that is with decrease in cases, average returns go up, for quarter 2 and 3 in 2020. Following which, they show positive correlation with the cases before again reverting to opposite response in second quarter of 2021, and finally two of the four firms finishing 2021 with a positive correlation and two firms with negative correlation. The fifth firm, Tata motors on the other hand displays a positive correlation with daily infections throughout 2020, that is with increase in cases, the average returns go up, until second quarter of 2021 which is when it display a similar response to the other 4 firms and finally end 2021 with a positive correlation with daily infections (**Figure 4.7b**).

Change in means of Pharmaceutical firm returns exhibit different behaviour. Throughout the two year window, the average returns of all 4 pharmaceutical firms remain positive, with a sudden increase in second quarters of both years. Only in the last quarter does the average



return fall below 0, thus indicating that except for the last quarter in 2021, all Pharmaceutical firms were in upward trend (**Figure 4.8a**). No two firms seem to exhibit a similar nature in their movements. All 4 firms start with positive correlation in the first quarter of 2020 with a drop in the second quarter. 2 of the 4 firms, AstraZeneca and Pfizer maintain a negative correlation with daily infections from third quarter of 2020 to last quarter of 2021, Reddy's Laboratories from second quarter in 2021 to last quarter and Moderna also finishing the last quarter with a negative correlation (**Figure 4.8b**).

The three banking firms selected move hand in hand, responding to Covid in a similar fashion. Like indexes and Automobile sector, mean return of all three firms is positive and approximately 0 for the last two quarters of 2019, and drop significantly below 0 in the first quarter of 2020. Post that, mean returns for all three firms remain positive and observed a decline till last quarter of 2021 when they revert close to the pre event mean values (**Figure 4.9a**). When looking at correlation movements in **Figure 4.9b**, all three firms follow similar changes. In the first quarter of 2020, they have a negative but almost non-existent correlation and in the second quarter they have a positive correlation. Till the second quarter of 2021, correlation values witnessed a decline with 2 firms dipping below 0 in fourth quarter of 2020 and the last firm in the next quarter. In the third quarter of 2021, all firms moved from negative to positive correlation and maintain that in the last quarter of 2021.

The returns of two IT firms follow a similar pattern to Banking firms when observing the change in mean of returns. From **Figure 4.10a**, it can be seen that both firms have almost 0 mean return in third and fourth quarter of 2019 and dip below 0 in the first quarter of 2020. From second quarter of 2020 on-wards, the average returns over all quarters remain positive throughout, indicating that stock price moved upwards since the second quarter of 2020. From **Figure 4.10b**, it can be observed that there is a significant increase in correlation from first quarter to second quarter of 2020, and from then to second quarter of 2021, there is a decline in correlation with quarter 1 and 2 of 2021 having negative correlation between returns and daily infections and the last two quarters having positive correlation.

Overall, the change in mean of returns for 13 out of 17 series selected follow a similar pattern, that is with onset of Covid 19 in the first quarter of 2020, the returns dipped below 0 dragging the prices down and bouncing back up to positive average returns from second quarter of 2020 till the last quarter of 2021. This indicates that any significant negative impact Covid 19 had on the financial markets was absorbed in the prices by the second quarter of 2020. The 4 pharmaceutical firms however do not show negative average returns over three quarters in any of the 8 quarters considered, thus indicating that a pandemic shock effect does not effect pharmaceutical firms negatively, rather it propels their prices in the anticipation of cure and containment. Correlation with daily infections on the other hand has no consistent pattern across the different sectors, except between firms within a sector.

	S&P500	DJIA	BSE
mean ( $10^4$ )	7.47	4.6	7.24
sd ( $10^2$ )	1.6632	1.7523	1.6326
skewness	-1.0394	-1.0343	-1.7496
kurtosis	17.5332	19.384	19.8761
z_max	5.3473	6.1167	5.2202
z_min	-7.7201	-7.9255	-8.6822

Table 4.1: Descriptive Statistics for stock returns of In scope Indexes from period 14/01/2022 - 31/12/2021

The case study thus implements a methodology to test if the number of daily infections can be treated as proxy for the event to study its impact on the financial markets, treating the log difference of daily cases as the shock variable and daily returns series of index and firms as a proxy for the financial markets. Along with that, first two stylized facts according to Taylor [2005], that is non normality of returns and no auto-correlation in 5 day lags, which are found to be present in return series across time and different markets, is also established.

## 4.2 Descriptive Statistics and Stylized Facts

Descriptive statistics are obtained for the stock returns at the index level as well as the stock level, to understand the distribution of series for the period of study, and are compared with pre-event window statistics. The following descriptive statistics as described in Chapter 3 are derived:

1. Mean
2. Standard Deviation
3. Skewness
4. Kurtosis
5. Z score Range (Min and Max)

### 4.2.1 Stylized Fact 1 - Test of normality in Daily Return Series

#### Index Level Descriptive Statistics

Descriptive statistics of stock returns for the selected indexes, which are Standard and Poor's 500 or S&P500, Dow Jones Industrial Average or DJIA and Bombay Stock Exchange or BSE, between the event period considered for this research are derived (**Table 4.1**). From that, it can be seen that all the three selected indexes have a mean and standard deviation of approximately 0, meaning that majority of the daily returns are centered around 0 and on an

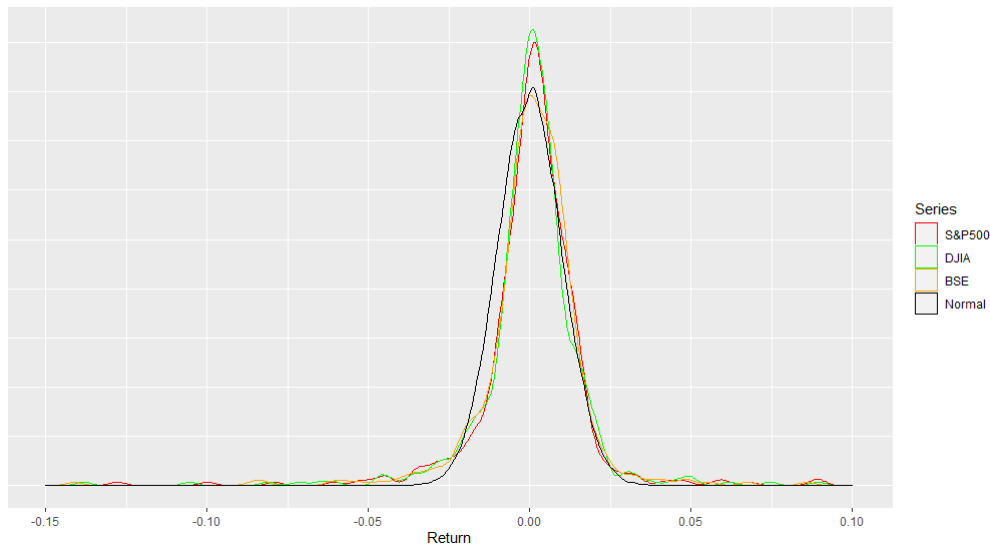


Figure 4.11: Density Plot: Index Daily Stock Returns vs Normal Distribution

average the stock returns or changes in next day price of the index is very marginal. The Skewness of the distribution tells us the symmetric or asymmetric nature of a distribution with respect to a normal distribution. A negative value means that the distribution has more values lesser than 0 and a positive value means that it has more values greater than 0. It can be observed that all three indexes have a negative skewness meaning that daily returns for the time period have more negative values and that prices have dropped more often than they have climbed up. Kurtosis of a distribution tells us about the heaviness of tails of the distribution, that is, how many extreme values are there in the distribution. If a distribution has kurtosis greater than 3, it is defined as Leptokurtic distribution and has fat tails, meaning more extreme values and a kurtosis value less than 3 is defined as Platykurtic distribution having thin tails, and less extreme values. It can be observed that all three indexes have extremely large kurtosis, significantly higher than a normal distribution.

Density plots of return series of selected indexes along with a normal distribution, reveal that daily returns have a higher concentration of values around the mean and only follow the shape of a normal distribution approximately (**Figure 4.11**).

From **Table 4.1** and **Figure 4.11**, it can be observed that the return series have a higher peak around the mean value, indicating more concentration of values around the mean, asymmetric with respect to normal distribution and fatter tails, thus proving the first stylized fact that return series are non-normal in nature.

### Firm Level Descriptive Statistics

Next, descriptive statistics for in scope firms are analyzed to verify the non-normality of stock returns at firm level. **Table 4.2** shows the descriptive statistics for the 14 Individual firms selected from the Automobile, Pharmaceutical, IT and Banking sectors. From the table, it

Sector	Firm	mean( $10^4$ )	sd( $10^2$ )	skewness	kurtosis	z_max	z_min
Automobile	TTM	18.42	3.9863	-0.23	7.01	3.74	-5.02
	TM	5.56	1.6284	-0.10	7.92	5.58	-5.57
	F	16.74	3.1146	0.45	8.31	6.71	-3.80
	HMC	2.90E-01	1.9582	0.05	7.67	4.90	-4.79
	GM	10.64	3.2413	-0.40	9.28	5.58	-5.90
Pharmaceutical	MRNA	50.88	5.7058	0.18	5.21	4.21	-3.56
	RDY	9.32	1.9659	-0.54	9.59	4.25	-6.77
	AZN	4.32	1.8994	-0.45	8.41	4.18	-5.93
	PFE	10.77	1.9765	0.23	7.42	5.16	-4.13
IT	INFY	17.79	2.257	-0.19	8.94	5.13	-5.77
	WIT	19.38	2.1283	0.09	6.47	4.52	-4.94
Banking	HDB	2.1	2.6845	-0.65	10.66	4.27	-6.62
	IBN	6.33	2.9643	-0.26	8.11	3.98	-5.10
	AXS	-1.33	2.4948	-1.22	11.84	3.66	-7.51

Table 4.2: Descriptive Statistics for stock returns of In scope Individual firms from period 14/01/2022 - 31/12/2021

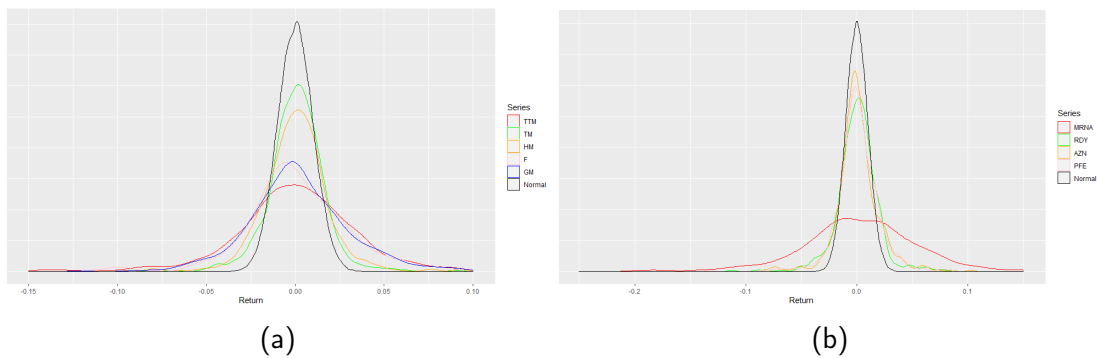


Figure 4.12: Density Plot: 4.12a shows the Automobile Daily Stock Returns vs Normal Distribution. 4.12b shows the Pharmaceuticals Daily Stock Returns vs Normal Distribution

can be seen that Mean and Standard deviation are very close to 0 for all 14 firms, 8 firms have significant negative and 3 have significant positive skewness, with 3 firms having almost symmetric distributions. All the series of 14 firms are leptokurtic in nature as they have significantly higher kurtosis than value of 3, which is the kurtosis of a normal distribution. Further, **Figure 4.12a**, **Figure 4.12b**, **Figure 4.13a** and **Figure 4.13b** compare the distribution shapes using density plots of daily returns of the 14 individual firms with normal distribution, split according to the sector, and it can be seen that all 14 series are only similar to normal distribution but not a normal distribution, thus proving that all 14 series conform to the first stylized fact.

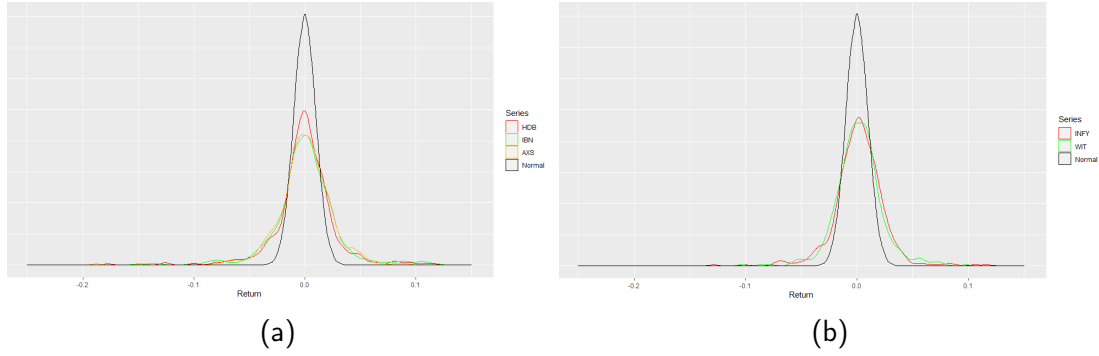


Figure 4.13: Density Plot: 4.12a shows the IT Daily Stock Returns vs Normal Distribution. 4.12b shows the Banking Daily Stock Returns vs Normal Distribution

## 4.2.2 Stylized Fact 2 - Minimum or No Auto-correlation in daily return series

The second stylized fact of daily return series is defined as returns have almost no correlation between different days lags. Correlation between different days lags is found using the following correlation formula :

$$\rho_{\tau,r} = \frac{\sum_{t=1}^{n-\tau} (r_t - \bar{r})(r_{t+\tau} - \bar{r})}{\sum_{t=1}^n (r_t - \bar{r})^2} \quad (1)$$

where correlation or dependence of return at time  $t$  is calculated with return at time  $t + \tau$ . Based on previous research highlighted in (Taylor [2005]), we calculate the correlation of returns at time  $t$  with up to 30 lagged values of itself. All 17 series, 3 Indexes and 14 individual firms are evaluated together for this part.

Correlation values of each of the 17 series is extracted for all lags between 1 and 30 trading days (**Table 4.3**). The first column shows the series name, the second segment of the table or Auto-correlation Lags show the correlation values for the first 5 days and the last segment which is Correlation frequency category shows the number of lags based on the correlation value, segment as follows, where  $\hat{\rho}$  is the correlation value:

1.  $\hat{\rho} < -0.1$
2.  $-0.1 \leq \hat{\rho} < -0.05$
3.  $-0.05 \leq \hat{\rho} < 0$
4.  $0 \leq \hat{\rho} < 0.05$
5.  $0.05 \leq \hat{\rho} < 0.1$
6.  $0.1 \leq \hat{\rho}$

	Autocorrelation Lags					Correlation Frequency Category					
	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	1	2	3	4	5	6
S&P500	-0.31	0.25	-0.03	-0.10	0.13	7	4	4	6	3	6
BSE	-0.09	0.02	0.02	0.03	0.21	2	5	7	8	5	3
DJIA	-0.23	0.24	-0.02	-0.10	0.15	6	6	5	4	4	5
TTM	-0.08	0.09	0.06	0.02	0.12	1	4	6	7	6	6
TM	-0.09	0.13	-0.10	-0.15	0.04	1	5	11	9	2	2
F	0.03	-0.00	0.02	-0.07	-0.06	0	4	11	9	3	3
HMC	-0.04	0.00	-0.04	-0.11	0.09	1	6	8	11	3	1
GM	-0.01	0.07	0.01	-0.10	-0.02	1	7	9	6	5	2
RDY	-0.06	0.08	0.05	-0.02	-0.02	2	3	14	8	3	0
PFE	-0.16	0.04	0.10	-0.04	0.05	2	5	8	8	5	2
MRNA	0.06	-0.08	0.08	0.09	-0.08	1	7	8	8	6	0
AZN	-0.18	0.11	-0.03	-0.06	0.08	4	4	8	8	4	2
HDB	-0.08	0.09	-0.04	-0.11	0.06	5	4	4	8	7	2
IBN	-0.04	0.09	0.01	-0.06	0.05	3	7	6	6	7	1
AXS	-0.07	0.14	-0.00	-0.03	0.05	2	5	8	6	6	3
INFY	-0.11	0.14	-0.04	-0.03	0.02	2	5	9	9	2	3
WIT	-0.05	0.08	0.03	-0.04	0.05	0	5	11	11	3	0
All Series Average	-0.09	0.09	0.00	-0.05	0.05	41	88	140	136	79	47

Table 4.3: Auto-correlation for Returns in all 17 series for the time period 14-01-2022 to 31/12/2021.

Last row in the table or All series Average shows the average correlation across the 17 series for the first 5 lags as well as the total count in each category.

It can be seen from the table that the estimated values of the auto correlation have very low numerical values. Only 89 of the total 510 estimations had values that are slightly less than -0.01 or slightly higher than 0.1; this represents a percentage of the values that is less than 18 percent. The general average of initial five day lags are extremely small, which establishes the second stylized fact, that returns have essentially little to no auto-correlation across various days.

When viewed cross section-ally, Indexes have the largest proportion of auto-correlation -0.1 or >0.1, which accounts for roughly 33 percent of the estimations. The automotive industry has only 18 out of 150 estimates in those categories, which is equivalent to 12 percent, while the pharmaceutical industry accounts for approximately 10 percent, which is equivalent to 13 out of 120 estimates; the information technology industry has only 11 out of 60 which account for almost 19 percent; and the banking industry has only 10 out of 90 which accounts for 11 percent. The conclusion that can be drawn from this is that although the overall auto-correlation is nearly non-existent, the indexes on their own exhibit greater than average auto-correlation in the 30 day interval during the event period considered.

	Autocorrelation Lags					Correlation Frequency Categories					
	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	1	2	3	4	5	6
S&P500	0.5267	0.6313	0.4908	0.4920	0.4394	0	0	0	0	6	24
BSE	0.3262	0.4735	0.3764	0.3336	0.3333	0	0	0	1	4	25
DJIA	0.5311	0.6061	0.5063	0.4931	0.4412	0	0	0	0	4	26
TTM	0.2508	0.2365	0.2465	0.1933	0.1401	0	0	0	4	10	16
TM	0.2799	0.2793	0.2928	0.1781	0.2421	0	0	7	8	3	12
F	0.2164	0.2010	0.1443	0.1883	0.2123	0	0	2	6	7	15
HMC	0.2115	0.2330	0.1969	0.1860	0.1795	0	0	1	6	6	17
GM	0.2088	0.3021	0.2385	0.2942	0.1965	0	0	2	2	6	20
RDY	0.2617	0.2282	0.1457	0.0895	0.0914	0	0	0	7	13	10
PFE	0.2672	0.3052	0.2758	0.2308	0.2758	0	0	1	5	7	17
MRNA	0.2252	0.0706	0.0847	0.0616	0.1214	0	1	7	11	9	2
AZN	0.2416	0.2864	0.2061	0.1763	0.1803	0	0	5	5	10	10
HDB	0.3897	0.4445	0.4296	0.3248	0.3855	0	0	0	2	4	24
IBN	0.2506	0.3299	0.3297	0.2393	0.3643	0	0	0	1	3	26
AXS	0.2709	0.3434	0.3810	0.1557	0.3555	0	0	0	2	3	25
INFY	0.3302	0.2705	0.2732	0.1677	0.1836	0	0	3	4	5	18
WIT	0.1989	0.1293	0.1418	0.1248	0.0429	0	0	7	13	5	5
All Series	0.2934	0.3159	0.2800	0.2311	0.2462	0	1	35	77	105	292

Table 4.4: Auto-correlation for absolute Returns in all 17 series for the time period 14-01-2022 to 31/12/2021.

### 4.2.3 Stylized Fact 3 - Positive dependence on nearby days in Transformed Returns

According to the third stylized fact about returns, squared and absolute returns have a positive dependence on nearby days, that is such series of transformed returns exhibit auto correlation. Using 1, correlation between transformed return series and its 30 days lags are analyzed in the same fashion as in 4.2.2.

**Table 4.4** and **Table 4.5** present the auto correlation values of transformed returns, absolute and squared returns respectively. Columns 2 to 6 present correlation values between transformed returns and first 5 lags, and the next 6 columns present the frequency of correlation values split into 6 categories defined below:

1.  $\hat{\rho} < -0.1$
2.  $-0.1 \leq \hat{\rho} < -0.05$
3.  $-0.05 \leq \hat{\rho} < 0$
4.  $0 \leq \hat{\rho} < 0.05$
5.  $0.05 \leq \hat{\rho} < 0.1$

	Autocorrelation Lags					Correlation Frequency Categories					
	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	1	2	3	4	5	6
S&P500	0.5085	0.5667	0.3348	0.3261	0.3238	0	0	0	11	2	17
BSE	0.1785	0.3483	0.2415	0.1598	0.3159	0	0	3	10	3	14
DJIA	0.4247	0.5823	0.3618	0.3364	0.3427	0	0	0	10	4	16
TTM	0.2811	0.2712	0.2715	0.1348	0.1282	0	0	1	11	10	8
TM	0.3077	0.2636	0.3674	0.1678	0.1926	0	0	12	2	3	13
F	0.2035	0.1105	0.0583	0.2200	0.1280	0	0	3	12	7	8
HMC	0.1644	0.1987	0.1947	0.0857	0.1668	0	0	3	5	8	14
GM	0.1235	0.3468	0.1637	0.4466	0.1552	0	0	2	10	6	12
RDY	0.1272	0.1462	0.0518	0.0355	0.0417	0	0	4	19	5	2
PFE	0.2696	0.2853	0.2468	0.1729	0.1832	0	0	5	9	4	12
MRNA	0.2550	0.0596	0.0750	0.0533	0.1385	0	0	9	12	5	4
AZN	0.2690	0.3467	0.2293	0.1180	0.1350	0	0	8	8	6	8
HDB	0.4157	0.5550	0.5190	0.3186	0.3829	0	0	0	7	10	13
IBN	0.2065	0.3940	0.3276	0.2196	0.4037	0	0	0	3	6	21
AXS	0.1154	0.4043	0.3028	0.0237	0.2806	0	0	1	13	7	9
INFY	0.2470	0.3135	0.1848	0.1101	0.1520	0	0	5	7	2	16
WIT	0.1695	0.2300	0.1501	0.0858	0.0869	0	0	14	7	6	3
All Series	0.2510	0.3190	0.2400	0.1773	0.2093	0	0	70	156	94	190

Table 4.5: Auto-correlation for squared Returns in all 17 series for the time period 14-01-2022 to 31/12/2021.

#### 6. $0.1 \leq \hat{\rho}$

When looking at auto correlation values between absolute returns, it can be seen that 464 out of 500 or approximately 93 percent of values are positively correlated with almost 400 values above 0.04. Further, the average auto correlation across all 17 series ranges between 0.25 to 0.32 for the first 5 lags. This indicates that there is a positive dependence of absolute returns on its previous days lagged values.

Cross sectional analysis shows that Index and Banking sector have no negative correlation on absolute returns over the first 30 days, Automobile sector having 15 out of 150 or 10 percent lags with negative correlation, followed by Pharmaceutical sector with 16 out of 120 or approximately 13 percent lags having negative correlation and lastly, IT sector having 10 out of 60 or almost 17 percent lags with negative correlation.

Similarly, when looking at auto correlation values between absolute returns, it can be seen that 430 out of 500 or approximately 86 percent of values are positively correlated with almost 300 values above 0.04. Further, the average auto correlation across all 17 series ranges between 0.17 to 0.32 for the first 5 lags. This indicates that there is a positive dependence of absolute returns on its previous days lagged values.

Cross sectional analysis of auto correlation on squared analysis reveals that IT sector



Model (Return as dependant variable)	Equation
with 5 days lagged values	$r_t = \alpha + L_5\beta r_t + \epsilon$
with 5 days lagged values and Daily Covid Cases	$r_t = \alpha + L_5\beta r_t + \gamma CC_{19} + \epsilon$
with 5 days lagged values and Log Change in Covid cases	$r_t = \alpha + L_5\beta r_t + \gamma LCC_{19} + \epsilon$

Table 4.6: Models Used for Statistical analysis

again has the highest percentage, approximately 30 percent, of negative correlation values with previous days, followed by Pharmaceutical sector having 26 out of 120 or approximately 21 percent, Automobile having 19 out of 150 or 13 percent and Banking and Index having 1 and 3 lagged days having negative correlation respectively.

Overall, it can be said that all 17 series exhibit the third stylized fact that transformed returns show a positive dependence on previous days lags, with IT sector having the least positively associated transformed returns amongst the five sectors.

### 4.3 Statistical Analysis

In this section, results from uni variate and bi variate regression models are analyzed to study the impact of Covid 19 daily infections on daily returns for the selected 17 series. One uni variate and two bi variate auto regression models are built and analyzed cross section-ally. The models used are defined in **Table 4.6**:

First, an auto regression model is built with return as the dependent variable and 5 days lagged value of the return as the independent variable. Next, the model is tested with daily recorded cases of Covid 19 as the dependent variable along with the 5 day lagged values and finally, daily recorded cases of Covid 19 is substituted with log change in daily cases of covid 19. Using the models, statistical significance of proposed proxy of the event variable is evaluated to infer if it can be used as a reliable source to study the impact of any future such events. The results are presented in panel format, comparing the results from all three models for each series, retaining only coefficients of independent variables that have been identified as statistically significant, that is the effect of those variables is not by chance. Appendix can be referred for the entire set of results from the three models. Statistical significance of variables is determined at three levels as follows:

1. \*\*\* : Significant at < 0.001 level
2. \*\* : Significant at < 0.01 level
3. \* : Significant at < 0.05 level

At an index level, *S&P500* has Lag 1 and Lag 2 values which are statistically significant at 0.01 level, however they are opposing in nature, that is Lag 1 has a positive impact and

Coefficients	S&P500			DJIA			BSE		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Lag 1	-0.2549 *	-0.2574 *	-0.2571 *						
Lag 2	0.2126 *	0.2094 *	0.2117 *	0.2399 *	0.2371 *	0.2391 *			
Lag 3									
Lag 4									
Lag 5							0.2154 *	0.215 *	0.2188 *
Intercept									
Covid Cases									
Covid Cases Log Difference									
Adj R2	0.1436	0.1438	0.1430	0.1373	0.1372	0.1370	0.0464	0.0450	0.0451

Table 4.7: Panel Regression: Comparison of results from three models for selected Indexes

Lag 2 has a negative impact. Dow Jones Industrial average has only Lag 2 as significant at the 0.01 level and Bombay Stock Exchange has only Lag 5 significant at 0.01 level. When comparing Adjusted  $R^2$  values for all three indexes across all three models, the value drops on adding the shock variables thus indicating that the two variables selected do not help explain the variability in the index daily returns. (**Table 4.7**)

At the firm level within the automobile sector, Tata Motors is positively affected by its 4<sup>th</sup> lag and Toyota Motors has opposing effects from 2<sup>nd</sup> and 4<sup>th</sup> day lags, the other three automobile firms show no dependence on their previous day lags. AstraZeneca and Pfizer show a negative dependence with only the day 1 lag. Information Technology and Banking do not show any dependence with their previous day lags (**Table 4.8**). While the addition of Covid Cases volume in Toyota Motors and Pfizer improved the model  $R^2$ , the shock variable itself was not significant and thus it can not be inferred that Covid Cases volume help explain the variance. Similarly, the addition of log difference of Covid Cases volume in Tata Motors, Toyota Motors, AstraZeneca and Pfizer improved the model  $R^2$ , the shock variable itself was not significant and thus it can not be inferred that Log Difference in Covid Cases help explain the variance for these firms. However, the addition of Log difference in Covid cases as the shock variable for Honda Motors, General Motors and Reddy's Laboratories improved the Adj  $R^2$  as well as had the coefficient of shock variable as statistically significant, that is the impact determined by the model was not by chance, and thus it can be inferred that that Log Difference in Covid Cases help explain the variance for these firms.

From the results, it can be seen that using volume of daily infections as a proxy for the pandemic over the period of two years for the selected sectors and indexes is not a viable option for the study of impact of related shock events, as the results are not statistically significant at any level. On the other hand, using the log difference of daily cases or infections of Covid has been found to have a statistically significant impact on the next day returns, thus such a control variable can be used to study the impact on returns at individual firm level.

Coefficients	TTM			TM			HMC		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Lag 1									
Lag 2				0.1408 *	0.1386 *	0.1426 *			
Lag 3									
Lag 4				-0.1781 **	-0.1803 **	-0.1811 **			
Lag 5	0.1153 *	0.1152 *	0.1146 *						
Intercept									
Covid Cases									
Covid Cases Log Difference									-0.0045 *
Adj R2	0.0235	0.0217	0.0248	0.0524	0.0528	0.0525	0.0122	0.0111	0.0145
Coefficients	GM			RDY			AZN		
Lag 1	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Lag 2							-0.1636 **	-0.1637 **	-0.1661 **
Lag 3									
Lag 4									
Lag 5									
Intercept									
Covid Cases									
Covid Cases Log Difference			-0.0073 *			0.0054 *			
Adj R2	0.0059	0.0059	0.0080	0.0034	0.0013	0.0075	0.0380	0.0361	0.0386
Coefficients	PFE								
Lag 1	Model 1	Model 2	Model 3						
Lag 2	-0.1552 *	-0.1581 *	-0.1556 *						
Lag 3									
Lag 4									
Lag 5									
Intercept									
Covid Cases									
Covid Cases Log Difference									
Adj R2	0.0280	0.0295	0.0299						

Table 4.8: Panel Regression: Comparison of results from three models for selected Firms

# Chapter 5 - Conclusion

## 5.1 Summary and Findings

This research is an attempt to map and computationally understand the impact of shock events variables, that is Covid 19 pandemic, on Indexes as a whole and individual firms. The results are obtained by statistically modelling the Covid cases volume and log difference of Covid cases volume with daily stock returns. Efficient Market Hypothesis, which states that all the information regarding a stock is in the price at any given and only new information causes the prices to fluctuate, is used as a baseline to understand the information flow disruption due to fake news and general panic in the investor behaviour as a result of Covid 19. A lot of research has been done as a part of this study to understand the basics of shock events and event study methodology, and stock market workings.

On the technical side, several tools and software were explored to build the pipeline for this study and perform the statistical analysis. R programming environment was used to for to build the data pipeline including data extraction, transformation and aggregation. It was also used for statistical modelling as it provided easy to use packages for this purpose such as `lmtest`, `vars` and `quantmod`, as well as several visualizations with the help of `ggplot2` package. Tableau was used for visual analysis and Excel was used, in addition for visual analysis, for panel study.

The case study selected for this research revealed statistically significant results, laying the ground work for future work on this subject.

## 5.2 Future Work

The current research has a scope for further improvement and the potential future work is described in this section. Based on the results obtained, the models can be expanded to include lagged values of log difference of shock variable to study the existence of a delayed dependence on the stock returns. Along with that, as the Covid 19 event has been found to

impact nearly all sectors and economies, the study can be expanded to include other markets and firms from different sectors to get a more holistic picture of the impact Covid 19 had on the financial markets as a whole.

Another research in the domain of understanding the disruption of information flow through the identification and classification of informative and fake news related to Covid 19 is ongoing at Trinity College Dublin by Muvazima Mansoor under the supervision of Dr. Khurshid Ahmad. Under the research, news articles spanning the years 2020 and 2021 are being examined for classification under the informative and fake news umbrella. In the immediate future, a collaborate effort to study the statistical significance of news articles related to shock events in understanding the effect on stock markets has been proposed.

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# Appendix

	Lag_1	Lag_2	Lag_3	Lag_4	Lag_5	Intercept	Adj R2
Index	<b>-0.2549 *</b>	<b>0.2126 *</b>	0.0407	-0.1322	0.0599	8.00E-04	0.1436
	-0.2182	<b>0.2399 *</b>	0.021	-0.1379	0.0797	5.00E-04	0.1373
	-0.1007	0.0057	0.0256	0.0542	<b>0.2154 *</b>	6.00E-04	0.0464
Automobile	-0.0904	0.0738	0.0719	0.0367	<b>0.1153 *</b>	0.0015	0.0235
	-0.0725	<b>0.1408 *</b>	-0.0971	<b>-0.1781 **</b>	0.0429	6.00E-04	0.0524
	0.0244	-0.0028	0.0203	-0.0702	-0.0523	0.0018	-0.0013
	-0.0313	0.0017	-0.048	-0.1083	0.0821	1.00E-04	0.0122
	-0.0139	0.0754	0.0076	-0.1028	-0.0267	0.0011	0.0059
Pharmaceuticals	0.0758	-0.0735	0.0841	0.0753	-0.0754	0.0046	0.0199
	-0.0613	0.08	0.058	-0.0192	-0.0258	9.00E-04	0.0034
	<b>-0.1636 **</b>	0.0846	-0.0102	-0.0598	0.064	4.00E-04	0.0380
	<b>-0.1552 *</b>	0.0295	0.1041	-0.0059	0.0383	0.001	0.0280
IT	-0.0906	0.1345	-0.0216	-0.0517	0.0179	0.0018	0.0209
	-0.0424	0.0827	0.0309	-0.0394	0.0406	0.0018	0.0027
Banking	-0.0658	0.0979	-0.0403	-0.1204	0.0503	3.00E-04	0.0219
	-0.0344	0.0981	0.0089	-0.0684	0.0388	6.00E-04	0.0063
	-0.0605	0.1472	0.0056	-0.0485	0.0482	-1.00E-04	0.0195

Table A1.1: Auto Regression results from Model 1 : Returns with 5 day lags.

	Lag_1	Lag_2	Lag_3	Lag_4	Lag_5	(Intercept)	new_cases	Adj R2
Index	S&P500	<b>-0.2574 *</b>	<b>0.2094 *</b>	0.0374	-0.1355	0.0574	2.80E-09	0.143808162
	DJIA	-0.2205	<b>0.2371 *</b>	0.0184	-0.1407	0.0774	2.70E-09	0.13724948
	BSE	-0.1013	0.0050	0.0248	0.0537	<b>0.215 *</b>	5.40E-09	0.044993227
Automobile	TTM	-0.0907	0.0735	0.0717	0.0365	<b>0.1152 *</b>	8.50E-09	0.021732001
	TM	-0.0747	<b>0.1386 *</b>	-0.0989	<b>-0.1803 **</b>	0.0408	2.90E-09	0.052844804
	F	0.0207	-0.0069	0.0163	-0.0748	-0.0564	7.80E-09	0.001342027
Pharmaceuticals	HMC	-0.0321	0.0008	-0.0487	-0.1093	0.0813	2.10E-09	0.011064803
	GM	-0.0158	0.0735	0.0061	-0.1044	-0.0286	5.40E-09	0.00593604
	MRNA	0.0754	-0.0741	0.0837	0.0750	-0.0759	-3.50E-09	0.018181377
IT	RDY	-0.0613	0.0800	0.0580	-0.0192	-0.0258	0	0.001322447
	AZN	<b>-0.1637 *</b>	0.0843	-0.0104	-0.0600	0.0639	6.00E-10	0.036116313
	PFE	<b>-0.1581 *</b>	0.0257	0.0988	-0.0116	0.0339	4.30E-09	0.029528909
Banking	INFY	-0.0906	0.1345	-0.0216	-0.0516	0.0179	1.20E-09	0.018828265
	WIT	-0.0456	0.0796	0.0278	-0.0431	0.0370	1.49E-08	0.003514234
	HDB	-0.0662	0.0975	-0.0406	-0.1206	0.0500	8.70E-09	0.020489739
	IBN	-0.0365	0.0960	0.0071	-0.0705	0.0370	1.78E-08	0.006371697
	AXS	-0.0611	0.1465	0.0048	-0.0496	0.0472	7.70E-09	0.018008114

Table A1.2: Auto Regression results from Model 2 : Returns with 5 day lags plus Covid Cases Volume

	Lag_1	Lag_2	Lag_3	Lag_4	Lag_5	(Intercept)	COVID>Returns	Adj R2
Index	S&P500	<b>-0.2571 *</b>	<b>0.2117 *</b>	0.0403	-0.1342	0.0572	8.00E-04	-0.0019
	DJIA	-0.2196	<b>0.2391 *</b>	0.0201	-0.1404	0.077	5.00E-04	-0.0023
	BSE	-0.1024	0.0089	0.0239	0.0556	<b>0.2188 *</b>	6.00E-04	0.0011
Automobile	TTM	-0.0874	0.0681	0.0823	0.0334	<b>0.1146 *</b>	0.0014	0.0063
	TM	-0.0724	<b>0.1426 *</b>	-0.0988	<b>-0.1811 **</b>	0.0439	7.00E-04	-0.0026
	F	0.0239	-0.0033	0.0187	-0.0712	-0.0523	0.0019	-0.0046
Pharmaceuticals	HMC	-0.033	0.0024	-0.0502	-0.1113	0.0801	2.00E-04	<b>-0.0045 *</b>
	GM	-0.0163	0.0771	0.0058	-0.1069	-0.0307	0.0013	<b>-0.0073 *</b>
	MRNA	0.0769	-0.0712	0.0816	0.0723	-0.0744	0.0045	0.0048
IT	RDY	-0.0588	0.0846	0.0597	-0.0214	-0.0266	8.00E-04	<b>0.0054 *</b>
	AZN	<b>-0.1661 **</b>	0.0855	-0.0101	-0.06	0.0616	5.00E-04	-0.0031
	PFE	<b>-0.1556 *</b>	0.0295	0.1055	-0.0078	0.0361	0.0011	-0.0042
Banking	INFY	-0.0791	0.1235	-0.0122	-0.0561	0.0139	0.0017	0.0044
	WIT	-0.038	0.0784	0.0365	-0.0446	0.0393	0.0018	0.0032
	HDB	-0.0598	0.093	-0.0384	-0.1201	0.0523	2.00E-04	0.0033
AXS	IBN	-0.033	0.0966	0.011	-0.0689	0.0393	6.00E-04	0.0013
	AXS	-0.0608	0.1454	0.0069	-0.0467	0.0476	-2.00E-04	2.00E-04

Table A1.3: Auto Regression results from Model 3 : Returns with 5 day lags plus Log Change in Cases Volume