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# Impact of the COVID-19 epidemic on the aviation industry

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**Abstract**

In early 2020, with the rapid spread of the COVID-19 virus, governments of different countries banned all kinds of public transport to prevent the spread of the virus. In this study, we have analysed the effect of the pandemic on the stock prices of the aviation industry. Here, we have calculated the log return and volatility for the stock prices and checked if there is any difference in the means of that particular measure before and after the hit of the pandemic. As, it is found that, volatility is the measure affected by the pandemic, we have performed a time series segmentation of the volatility using the strucchange package in R and estimated the date(s) when the change in volatility occurred. We have also commented on the economic significance of those date(s) and discussed how these findings can be useful in practice.

**Key Words** : *Aviation, COVID-19, Log Returns, Stock Price, Structural Change, Volatility.*

## 1 Introduction

On 31st December 2019, the World Health Organization (WHO) was informed about a new case of pneumonia of unknown origin in Wuhan city which was later attributed to a novel coronavirus named **Severe Acute Respiratory Syndrome Corona Virus 2 (SARS-CoV-2)**, a new strain of coronavirus that had not previously been identified in humans. On 11th March 2020, the WHO director announced the outbreak of COVID-19 as a pandemic due to the rapid increase in the number of positive cases outside China [1].

The SARS-CoV-2 virus is primarily transmitted between people through respiratory droplets and contact routes [2][3] and hence, might pose a potential risk for COVID-19 control. To control the rapid spread of the virus, WHO suggests some basic preventative measures among which, maintaining social distance (approximately 2 meters) from individuals with respiratory symptoms is one of the most important. In response, world governments implemented strict nationwide lockdown as well as a ban on public transport system. International travelling was also affected as countries restricted the immigration of all international travellers. As a result of this, operation of the aviation industry virtually shut down and all its impact was reflected in the stock prices of different companies in the aviation industry. This paper [4] shows a detailed analysis of the impact of travel ban on the aviation sector.

Here, in this study, we consider a set of airlines companies, which operate their flight services internationally. Some companies are Indian origin but we have also considered others which operate flights to India. In this study, firstly, we will study the impact of the pandemic on log returns and volatility, two important measures of stock price variation.

## 2 Analysis of financial time series

A financial time series refers to data corresponding to a financial asset, which may be stock market index values, stock prices, exchange rates, gold prices etc, are recorded at a regular interval. We first define some terminology related to stock prices which we shall subsequently need for the analysis.

## 2.1 Return

The return is defined as a profit on an investment over a period of time. In general, it is expressed as a proportion of the investment. Returns of an asset are widely used instead of its price in financial studies. According to [5], the return is a complete and scale-free summary of an investment and being stationary, has convenient statistical properties.

### 2.1.1 Simple Return

Let, $P_t$ be the price of an asset at time index $t$ with an origin of 1st August, 2019. Then the *Simple Gross Return* of period one at time $t$ is defined as

$$1 + r_t = \frac{P_t}{P_{t-1}} \tag{1.1}$$

and the corresponding *Simple Net Return* or *Simple Return* of period one is defined as

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{1.2}$$

### 2.1.2 Log Return

The natural logarithm of the *Simple Gross Return* of an asset is called *Log Return* or the *Continuously Compounded Return*. Now, let $P_t$ be the price of an asset at time index $t$. Hence, the *Log Return* of period one at time $t$ is defined as

$$R_t = \ln(1 + r_t) = \ln\left(\frac{P_t}{P_{t-1}}\right) = \ln(P_t) - \ln(P_{t-1}) \tag{1.3}$$

The *Log Return* has a few advantages over the *Simple Return*. Multi-period log returns is simply the sum of log-returns of period one and logarithmic transformation leads to more tractable statistical properties. [6][7].

### 2.2 Volatility

Volatility is a statistical measure of the dispersion of returns for a given stock price or market index. A higher volatility means that a stock price can potentially be spread out over a larger range of values. This means that the price of the stock can change dramatically over a short time period in either direction. Lower volatility indicates that the price of a stock does not fluctuate dramatically, and tends to be more steady. A greater degree of volatility means there is a higher likelihood of large price movements which increases the risk and uncertainty associated with owning a security [8][9]. According to a study of Crestmont Research, there is a strong relationship between the volatility and the performance of the market. Volatility tends to decline as the stock market rises and tends to increase as the stock market falls [10], which means higher volatility indicates a declining market while lower volatility indicates a rising market [11].

In this study, we have used the following formula to calculate the volatility:

$$V_t = {R_t}^2 \tag{1.4}$$

## 3 Data

For this study, the daily stock price data of different airline companies has been downloaded from `https://www.investing.com/`. Some companies are of Indian origin (like **Indigo Airline**, **SpiceJet Airline**) and some originate from countries rather than India (like **Air Asia Airline**, **American Airlines**, **Delta Airlines**, **Deutsche Lufthansa Airline**, **Emirates Airline**, **Japan Airlines**, **Singapore Airlines**, **United Airlines**).

From the Figure 1 it can be observed that there is a sharp fall in the stock prices of Indian airline companies after the first COVID case has been officially reported. When 'Janta Curfew' was declared in the nation, the

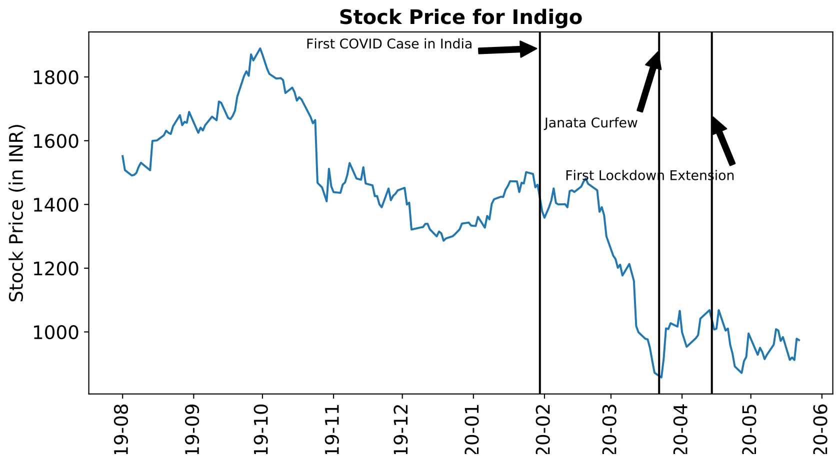


Figure 1: Stock Price of Indigo

percentage of decrease in the stock prices for the above two companies were 38.58 and 63.53 , respectively.

Figure 2 indicates that the stock prices of international airline companies with origin other than India are showing downward trends roughly between the last week of February and second week of March as the worldwide case count increases from 77,000 to 155,000 and the death toll increases from 2,000 to 6,000. In these three weeks, United Airlines experienced maximum decrement (55.34%), while Air Asia showed 52.77% decrease in its price, Singapore Airlines declined by 21%, American Airlines and Deutsche Lufthansa by 43.8% and Delta Airlines and Emirates by 39%. On 11th March 2020, the WHO declared the coronavirus outbreak as a pandemic.

## 4 Analysis

As we are interested in the relative changes in the stock price rather than the actual stock prices we use the log-returns of the price using the formula (1.3).

Figure 3 shows that there is no change in the means of log returns for

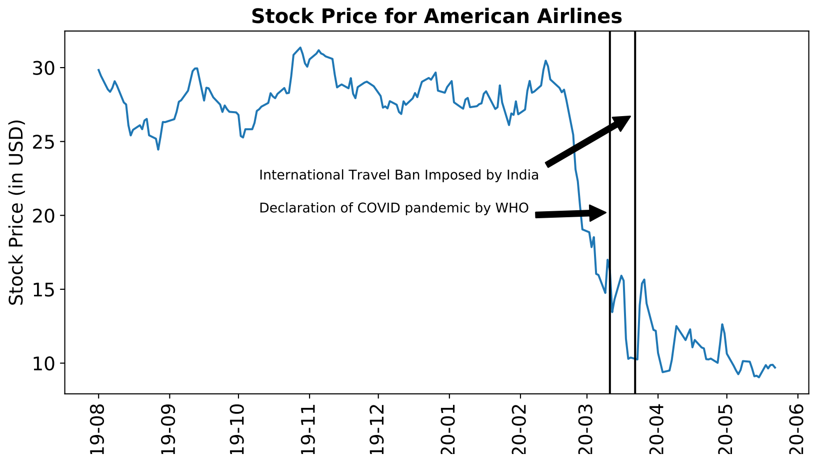


Figure 2: Stock Price of American Airlines

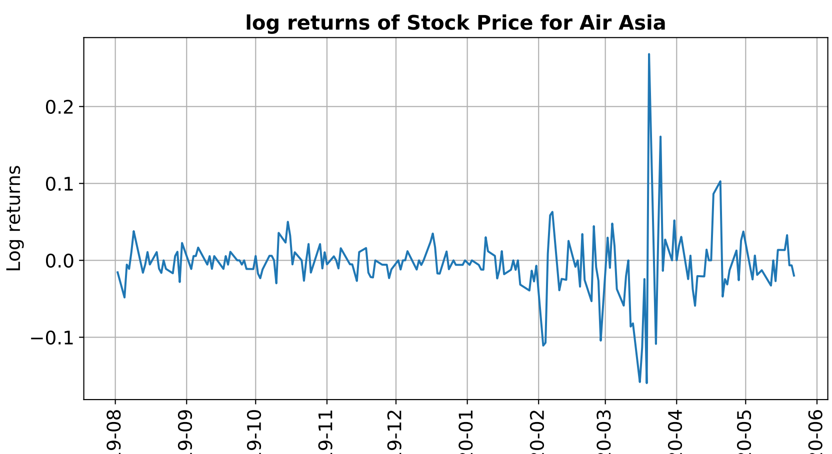


Figure 3: Log Return of Stock Price for Air Asia

any airline company, but from the 2nd half of February 2020 (or from March 2020), the rate of rise and fall in the stock prices has increased.

We wish to study whether there is a significant change in the stock prices after official reporting of the first coronavirus patient in India. In order to find the answer, we split the data on stock prices of Indian companies in two parts prior and post the corresponding date, 30th January 2020. We perform a t-test to test for significant difference between the mean log returns. Now, although the stock prices exhibit auto-correlation, the log returns are serially uncorrelated [12] and as the log-returns follow Normal Distribution, a t-test can be used. The null hypothesis of interest, "There is no difference between the means of the two subseries" and in each case, we fail to reject the null hypothesis. We have also performed the above test while dividing the data sets with respect to the date of the Janta Curfew Date (22nd March 2020) and 1st declaration of lockdown extension (14th April 2020), but all of these tests give the same result. Only SpiceJet shows a significant increase in the relative change after the 22nd March (Date of Janata Curfew and International travel ban imposed by India).

For the other airline companies that originate outside India, we have performed the same test using the data of WHO's global pandemic announcement (11th March 2020) and India's imposition of a ban on international traffic (22nd March 2020). In each case, we fail to reject the null hypothesis.

However the graphs of log returns clearly indicate that there is increased variability in the rate of change of stock prices of the airline companies after January 2020. So, though the relative change in price has not been significantly affected due to the COVID-19 pandemic, the volatility (i.e., variability in the rate of change) has increased. We calculated the volatility of the data using the formula (1.4) and plotted these on a graph, clearly indicating that towards the end of February 2020 all companies have lost the stability in stock prices. A few companies have also been able to return to stability with comparatively lower stock price at the start of April. To test that, we performed Student t-test on the volatility values by splitting the dataset as before. All airline companies of Indian origin show significant differences in volatility pre and post 30th January 2020, the date on which the first COVID case was reported in India. All foreign companies show significant differences in volatility pre and post 11th March, 2020, the date of the pandemic announcement.

To get a clearer idea of the exact date of change, we estimate it from the data using `R` package named `strucchange` [13]. Using the function *breakpoints* [14] from this package we have found the date(s) of structural change in volatility for each dataset. The function uses piecewise linear models and dynamic programming to find $m$ breakpoints which minimize the residual sum of squares (RSS) . The Bayesian Information Criterion (BIC) is used to find an optimal model as a compromise between RSS and the number of parameters. The test for significant changes in the time series is done by the ordinary least-squares residual-based moving sum (OLS - MOSUM) [15]. If changes are detected, the number and position of breakpoints are estimated [16].

Table 1 shows the estimated dates of changes for each airline company.

Table 1: Estimated Dates of Changes for each airline company

| Country | Date 1 | Date 2 |
|---|---|---|
| Air Asia Airline | 31-01-2020 | 25-03-2020 |
| SpiceJet Airline | 19-02-2020 | 03-04-2020 |
| American Airlines | 21-02-2020 | 03-04-2020 |
| Delta Airlines | 21-02-2020 | 03-04-2020 |
| Deutsche Lufthansa Airline | 21-02-2020 | 06-04-2020 |
| Emirates Airline | 27-02-2020 | 09-04-2020 |
| United Airlines | 27-02-2020 | 09-04-2020 |
| Japan Airlines | 05-03-2020 | |
| Singapore Airlines | 06-03-2020 | |
| Indigo Airline | 09-03-2020 | |

Air Asia is the first company to experience significantly increased volatility from 31st February as total COVID positive cases crossed 10,000 marks in the world. On 19th February, SpiceJet experienced increased volatility. This corresponds to the time at which 528 new COVID cases had been confirmed worldwide, all of them from Asia and more specifically, this was the day when the maximum number of daily new cases had been reported outside of mainland China. Two days later, significant increase in volatility is observed for the three largest international airlines viz. American Airlines, Delta Airlines and the German airlines, Lufthansa. On this day, the Lufthansa Group announced extended service reduction in Mainland China and Hong Kong up to 29th March instead of 1st March as originally announced. We also observe that companies who experience an initial increase in volatility before the last week of February 2020 are able to regain stability around the first week of April but others experiencing increased volatility for whose volatility after the third week of February are not able to stabilise until the third week of May.

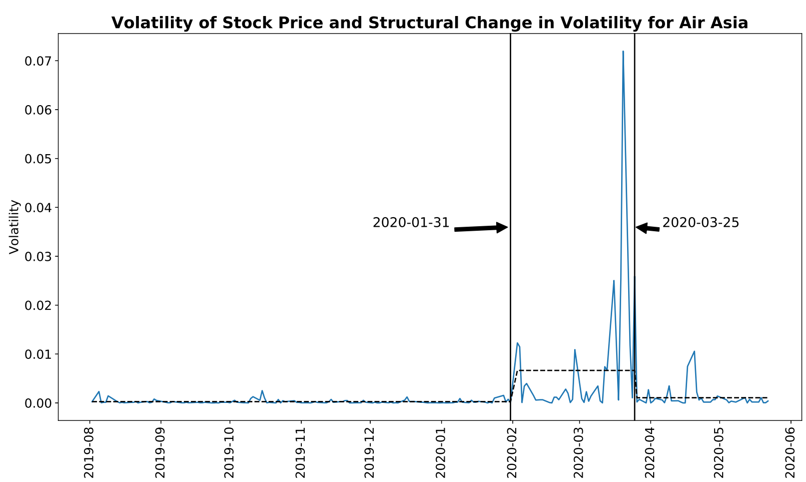


Figure 4: Volatility of Stock Price and Structural Change in Volatility for Air Asia

**Air Asia Airline:** The volatility in the stock price of Air Asia increased on 31st January 2020 and then decreased on 25th March 2020. In this context, on 18th February, the total confirmed COVID cases all over the world crossed 75,000 and the total death toll crossed 2,000.

**American Airlines:** There is a significant increase in volatility of American Airlines stock prices between 21st February to 3rd April. On 29th January, the company declared suspension of flights from Los Angeles to Shanghai and Beijing between 9th February to 27th March. It would maintain its flight schedules (10 daily A/R) from Dallas-Fort Worth to Shanghai and Beijing, as well as from Los Angeles and Dallas-Fort Worth to Hong Kong.

**Delta Airlines:** Delta Airlines experienced increased volatility from 21st February to 3rd April. It was the only company which did not change its schedule of direct flights from USA to China up to 29th January when the U.S. State Department issued a Level 4: Do Not Travel to China Alert (the highest level of alert).

**Deutsche Lufthansa Airline:** The stock price of Deutsche Lufthansa exhibits an increase in volatility on 21st February and it lasts for more than a month, and then from 6th April, a comparatively stable period.

**Emirates Airline:** For the largest airline in the Middle-East, Emirates, increased volatility starts from 27th February 2020. On 9th April, it recovers to enter a comparatively stable period.

**Indigo Airline:** Indigo, the largest Indian airline company, experiences increased volatility from 9th March 2020 lasting until the third week of May. In this context, on this day, India decided to send its one air force carrier for evacuating Indian citizens from COVID hit nations, while the worldwide death toll crossed 4,000 and confirmed cases has already crossed 100,000 three days earlier. In China, total deaths crossed 3,000 just one week earlier.

**Japan Airlines:** On 5th March of 2020, volatility in Japan Airlines's stock prices increased significantly with no observed decrement till 24th May

2020, at which point, total confirmed cases in Japan crossed 350.

**Singapore Airlines:** The stock price data of Singapore Airlines exhibits an increment in the volatility on 6th March 2020 and this does not decrease until 24th May.

**Spice Jet Airline:** The volatility in Spice Jet stock prices increased on 19th February and this lasts more for than one month up to 3rd April 2020.

**United Airlines:** For United Airlines, increased volatility starts from 27th February, followed by a comparatively stable period from 9th April. In this context, on 24th February, total active cases crossed 50 in the USA. On 28th January, the company declared that it would cut its 24 flights between USA and China from the first week of February 2020.

## 5 Conclusion

As expected, it is clear from the analysis that stock prices have fallen sharply after the COVID outbreak in late January of 2020. Our objective was to find how the aviation industry was affected due to COVID-19. Now, initially, one can expect that there would be a negative trend in the log-returns of the stock prices after the COVID outbreak, but the hypothesis was rejected as there is no difference in the means of log returns before and after the outbreak. But the variance in the log-returns has been increased since the second half of February 2020. In order to analyse this, we focus on volatility and found that there is a significant difference in the means of volatility before and after announcement of the COVID outbreak. We estimate the dates of structural change in volatility and find that for most of the airline companies, the period of increased volatility started in between the third week of February and the first week of March. This is followed by a comparatively stable period with low price for a few companies around the last week of March while some companies have as yet not been able to recover from their volatile period.

The main objective of this paper is to study the historical development of stock prices in the airline industry. The discoveries can be practically useful in certain ways

- A higher volatility translates to a higher option value. This is exactly true for implied volatility and empirically observed for historical volatility. Since many stocks have revived from high volatility, it is expected that the others will also revive. For the latter class of stocks, an investor can expect to make money by shorting options while the volatility is high and buying them when the volatility subsides. For example, a recommended position to take would be a short straddle.

- The aviation industry has been directly affected by the economic measures related to COVID-19. However, other sectors have also been affected eventually and it is likely that they will follow the same pattern, perhaps with a time lag. In follow-up work, we are studying if this is indeed the case and preliminary results do confirm this hypothesis. The option trading strategies can then be extended to other stocks.

- Instead of indirect trading through the options, the NVIX can be used to directly trade the volatility of the NIFTY index option prices.

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