Impact of Public Health Events on Aviation Stock Returns and Volatility: Evidence from COVID-19

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Abstract. The aviation industry was greatly impacted during COVID-19 since 2020. At the end of 2022, the epidemic was basically under control. In the post-epidemic era, the prevention and control policies were relaxed. The aviation industry gradually recovered. These events led to great influence to aviation stocks. To examine the influence of the pandemic on aviation stocks, the event study method and the GARCH model are adopted analysing the return and its volatility. The result indicates that the outbreak of the coronavirus brought about a detrimental impact on aviation stocks. During the epidemic, negative news had a greater impact than positive news, while in the period before the COVID-19 positive news exerted greater impact. Moreover, both persistence and long-term memory of the fluctuation decreased during the pandemic. The come of the post-epidemic era had a favourable influence on aviation stocks. Nevertheless, the effects of both events were relatively transient. These results help to guide aviation stock investment during public health events.

1 Introduction

The aviation industry is one of the pillar industries of a country and it is crucial to the development of the overall economy. It is also highly influenced by the economy. For example, it is closely related to global economic trends, exchange rates, oil prices, and geopolitical events [1]. It has been found that the stock returns of listed aviation companies have a negative price spillover effect [2]. In 2020, the outbreak of the novel coronavirus led to economic downturn, which had a negative impact to the aviation stock market [3]. At the same time, the aviation industry has suffered a huge impact since the coronavirus epidemic, as the number of travelers has dropped sharply due to the massive spread of the virus and the restrictions of anti-epidemic policies [4]. However, the aviation industry itself has problems such as high financial leverage, difficult cost control, and high liquidity risk. Therefore, this sudden wave forced many airlines to pay high debts and fell into the predicament of imminent breakage of capital chain [5].

Owing to the global economic recession and the downward performance of the aviation industry, most airlines and airports have experienced large declines in stock prices. Some stocks even fell below their historical lows [6]. As the epidemic slowly got under control, the economy gradually picked up [7]. Chinese government adjusted its epidemic prevention and control policies in late 2022. Aviation market in China is recovering [8]. For investors, there is some opportunity in the aviation stock market. However, the aviation industry still faces big challenges. The aviation industry still has not fully recovered to its pre-epidemic state, and the number of flights and passengers worldwide today is still far from the pre-epidemic level. It will be a long recovery process. However, in the long run, the global aviation industry still has a large potential for development, which also provides good opportunities for investors in aviation stocks, so it is worth to conduct relevant analysis and research.

Using CAPM model, event analysis method, and GARCH family model, Chen found that the pandemic caused an overall W-shaped fluctuation and a huge negative shock in the stock market in the short term [9]. Xia used TGARCH model finding out that the impact of the epidemic gradually diminished over time [10]. Jin used TVP-VAR model discovering that the impact of Shanghai, Wuhan, and Xi'an city closures on the stock market is short-lived [11]. Zhan analyzed the negative impact of the 2020 outbreak on the stock returns of aviation industry conducting the event study method [6].

In terms of the impact of coronavirus, most of the papers so far have looked at the overall stock market, but less research has been conducted on aviation stocks. This paper selects two major events of the epidemic for study, i.e., the outbreak of the epidemic and the start of the Post-epidemic era. Since it was only about seven months before epidemic prevention and control policies were adjusted in China, most papers focused only on the impact of the outbreak and lacked follow-up studies. Meanwhile, this paper examines both the aviation stock abnormal returns and volatility of returns.

2 Analysis of abnormal returns

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To explore the immediate impact of the coronavirus on aviation stock returns, event analysis is conducted to investigate whether there are abnormal returns and analyze the trend of abnormal returns.

2.1 Data selection and preparation

In accordance with the "Industry Classification Guidelines for Listed Companies" (revised in 2012) released by the China Securities Regulatory Commission, eleven companies in "Air Transportation" (G56) under the category of "Transportation, Storage and Postal" are selected. CITIC Oceanic Helicopters Co., Ltd. and Eastern Airlines Logistics Co. which are less related to civil aviation are removed. The full list of companies and their stock codes are shown in Table 1. Stock market trading data and Fama-French factor data were obtained from the Guotaian database (CSMAR) as is shown in Table 2.

Table 1. full name and stock code

Company full name	Stock code
Shenzhen Airport Co., Ltd.	000089
China Express Airlines Co., LTD	002928
Guangzhou Baiyun International Airport Co., Ltd	600004
Shanghai International Airport Co., Ltd.	600009
China Southern Airlines Co., Ltd.	600029
China Eastern Airlines Co., Ltd.	600115
Hainan Airlines Holding Co.,Ltd.	600221
Xiamen International Airport Co.,Ltd.	600897
Spring Airlines Co.,Ltd.	601021
Air China Ltd.	601111
Juneyao Airlines Co.,Ltd.	603885

Table 2. Field selection and abbreviations

Fields	Abbreviations
Stock Code	Stkcd
Transaction Date	TradingDate
Daily individual stock returns considering reinvestment of cash dividends	Dretwd
Market risk premium factor (market capitalization weighted by liquidity)	mkt_rf
Market capitalization factor (market capitalization weighted by liquidity)	smb
Book-to-market ratio factor (market capitalization weighted by liquidity)	hml

2.2 Definition of events

First, one sets the dates of January 20th, 2020 and December 7th, 2022, when the important events occurred, as event days. The former date represent the outbreak of COVID-19. The latter one means that epidemic prevention and control policies are soften representing the start of the Post-epidemic era. The detailed description is shown in Table 3. One selects 11 trading days as event windows, i.e., [T-5, T+5], and estimation windows of 200 trading days, i.e., [T-205, T-6].

Table 3. Event Definition

Event Day	Events
January 20th, 2020	COVID-19 was formally classified as a a legally recognized infectious disease by the State Council. Nanshan Zhong conclusively stated that the virus can be "human-to-human".
December 7th, 2022	The State Council Joint Prevention and Control Organization optimize the implementation of ten measures of the COVID-19 prevention and control: voluntary nucleic acid testing, elimination of Health code and travel card and etc.

2.3 Estimation of normal returns

First, the normal return is calculated using three-factor model proposed by Fama-French.

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{it} \quad (1)$$

Here, R_{it} signifies the return of i^{th} stock. R_{mt} represents the average market return. R_{ft} represents the risk-free rate of return. SMB_t denotes the market capitalization factor portfolio return. HML_t denotes the book-to-market portfolio return. β_i, s_i, and h_i denote the coefficients of the three factors.

2.4 Calculation of cumulative abnormal returns

Brown & Warner define the abnormal return of i^{th} stock in period t and the cumulative abnormal return of i^{th} stock in $[T, T+q]$ period. The abnormal rate of return(AR) is calculated using the following formula:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \quad (2)$$

Here, $R_{i,t}$ represents the actual return of the i^{th} stock at time t, and $E(R_{i,t})$ represents the expected return of the i^{th} stock at time t. The formula for calculating the cumulative abnormal return(CAR) is as follows:

$$CAR_{i,[T,T+q]} = \sum_{t=T}^{T+q} AR_{i,t} \quad (3)$$

2.5 Significance test

In order to observe the significance of results, t-test is conducted separately for the average abnormal return(AAR) and the average cumulative abnormal return(ACAR) with the following equation:

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} \mathrm{AR}_{i,t} \tag{4}$$

$$T_{AR_t} = \frac{AR_t}{\frac{\sqrt{Var(AR_t)}}{\sqrt{n}}} \tag{5}$$

$$ACAR_{[T,T+q]} = \frac{1}{N}\sum_{i=1}^{N} CAR_{i,[T,T+q]} \tag{6}$$

$$T_{CAR_{[T,T+q]}} = \frac{ACAR_{[T,T+q]}}{\frac{\sqrt{Var\left(ACAR_{[T,T+q]}\right)}}{\sqrt{n}}} \tag{7}$$

Here, Var() denotes the variance.

2.6 Analysis of empirical results

According to the theory of event study method, the average abnormal return and the average cumulative abnormal return of 11 samples within 2 event windows are calculated. T-test is performed to test whether results have significant difference from zero. The results are presented in Table 4.

Table 4. Empirical results of ACAR and its t-value

Events	Event 1		Event 2	
Time	Average cumulative abnormal return	t-value	Average cumulative abnormal return	t-value
T-5	-0.00906	-0.89216	0.015001	1.352532
T-4	-0.00892	-0.87865	-0.0116	-1.04628
T-3	-0.0118	-1.16246	-0.01192	-1.07459
T-2	-0.01702(*)	-1.67651	0.01178	1.062103
T-1	-0.02074(**)	-2.04268	0.016998	1.53256
T	-0.05003(***)	-4.92697	0.051126(***)	4.609658
T+1	-0.05918(***)	-5.82795	0.0525(***)	4.733526
T+2	-0.06502(***)	-6.40272	0.035473(***)	3.1983
T+3	-0.07196(***)	-7.08639	0.07079(***)	6.382593
T+4	-0.07991(***)	-7.86936	0.091705(***)	8.26835
T+5	-0.11467(***)	-11.2926	0.100674(***)	9.077015

***, **, * respectively represent that the reult is significant at the level of 1%, 5% and 10%.

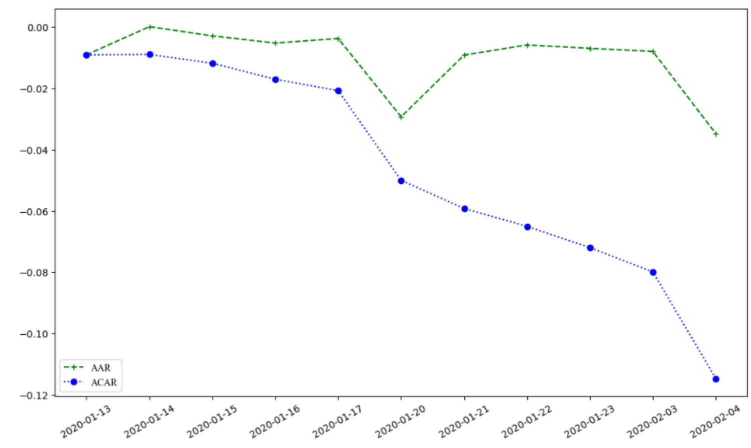

Fig. 1. AAR and ACAR of event 1 (Photo/Picture credit: Original).

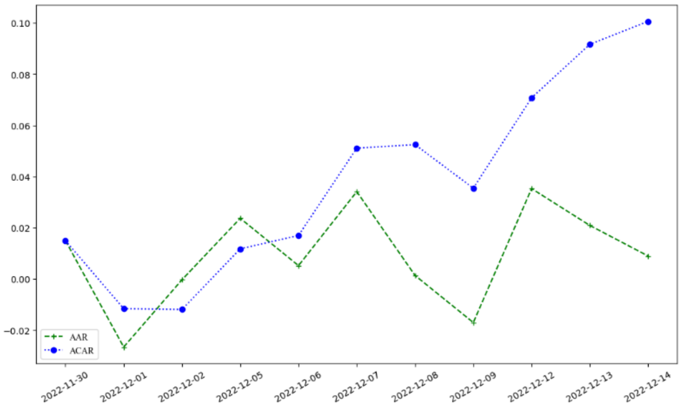

Fig. 2. AAR and ACAR of event 2 (Photo/Picture credit: Original).

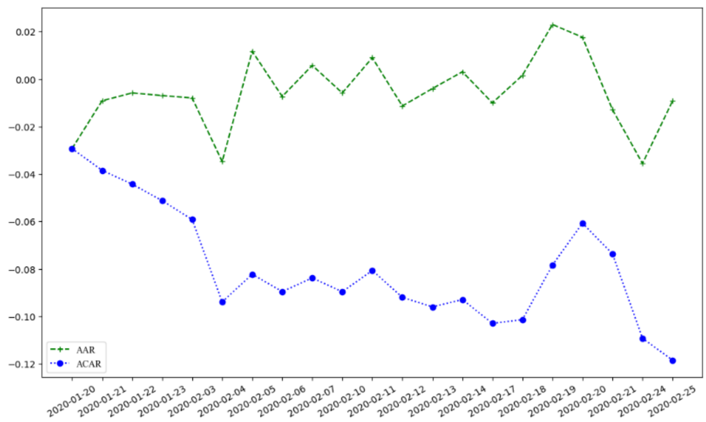

Fig. 3. AAR and ACAR of event 1 after event date (Photo/Picture credit: Original).

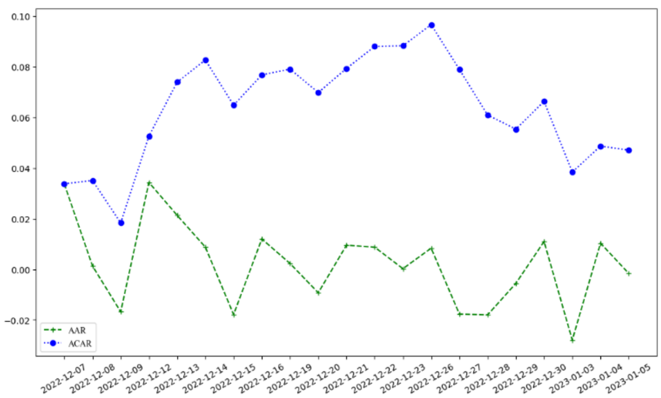

Fig. 4. AAR and ACAR of event 2 after event date (Photo/Picture credit: Original).

Event 1 represents the COVID-19 broke out in China in large scale. Fig. 1 illustrates that the epidemic had a significant negative impact on airline stock returns, making stock returns much lower than expected returns. The negative impact was most significant on the event date, but it was less significant before the event, which corresponds to the suddenness nature of the pandemic. The relatively weaker negative impact after the event may be due to the fact that it is in the pre-Spring Festival period. The Spring Festival mitigates some of the negative impact of the epidemic. Event 4 denotes the optimization of the epidemic prevention and control policy. Prevention and control are more scientific and precise, with less travel restrictions and gradual recovery of the airline industry. It represents the arrival post-epidemic era. Seen from Fig. 2, it can be found that it exerted positive impact on airline stock returns. In most of trading days in event window, the actual return is higher than expected stock returns.

In order to explore the duration of the impact of the outbreak, the abnormal returns and cumulative abnormal returns 20 trading days after the event date are also examined. The Fig. 3 and Fig. 4 show that the impact of two events on stocks are relatively short-lived. The sustained negative impact caused by Event 1 basically disappeared by the 5th trading day after event date(14 days later). The negative impact may even last much less than 14 days due to the lack of some data during the Chinese New Year holiday. The positive impact brought by Event 2 almost disappeared by the 13th trading day after event date(19 days later).

3 Analysis of returns volatility

To explore the volatility of airline stocks during the pandemic, a GARCH family model is built in this paper.

3.1 Main modelling methods

In this paper, GARCH(p, q) model is built. First, the conditional mean equation is established:

$$r_t = c_0 + \sum_{i=1}^{m} \phi_i r_{t-i} + \varepsilon_t \tag{8}$$

$$\varepsilon_t = \sqrt{\sigma_t{}^2} e_t \tag{9}$$

Here, r_t is the stock return, which is the observable term; ε_t is the residual term, which is the ARCH effect term; e_t is the white noise series, which satisfies the standard normal distribution; $\sigma_t{}^2$ is the conditional variance of the residual term, also known as the GARCH effect term. Subsequently, conditional variance equation is established.

$$\sigma_t{}^2 = w_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}{}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}{}^2 \tag{10}$$

The conditional variance is related to the lag of the residuals in the conditional mean equation and the lagged conditional variance of the residuals. α_i represents the sensitivity of the conditional variance to past volatility. If the value is greater than 0, it represents a significant increase in volatility; β_j $signifies$ how the conditional variance of the current period is affected by the conditional variance of the previous period. When the sum of α_i and β_j is near 1, it suggests a persistent volatility pattern and stability in the GARCH model.

The exponential autoregressive conditional heteroskedasticity model, EGARCH model(p,q,r), is an asymmetric GARCH model with the following conditional variance equation:

$$\log(\sigma_t{}^2) = w_0 + \sum_{i=1}^{p} \alpha_i \left(\left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| - E\left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right) \right) + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}{}^2) + \sum_{k=1}^{p} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \tag{11}$$

If $\gamma_k > 0$, it indicates that the effect of positive news on the conditional variance is greater than the effect of negative news. Larger γ_k indicates a more significant leverage effect of the return series.

Table 5. Descriptive statistics of CITIC Airline Index

period	N	MEAN	MEDIAN	MIN	MAX	STD	SKEWNESS	KURTOSIS	Jarque-Bera(p)
2016.1.4-2020.1.19	987	0.000104	0.000244	0.037768	-0.037486	0.007666	-0.028381	6.777433	586.9451(0.00)
2020.1.20-2022.12.6	698	0.0000488	-0.000233	0.029361	-0.045788	0.007989	-0.103530	5.071310	126.0239(0.00)

Table 6. ADF test results

period	ADF statistics	1%	5%	10%	P
2016.1.4-2020.1.19	-33.5454	-2.567309	-1.941145	-1.616483	0.0000
2020.1.20-2022.12.6	-24.76045	-2.568284	-1.941278	-1.616394	0.0000

Table 7. ARCH effect test results

2016.1.4-2020.1.19	F-statistic	5.169033	Prob. F(10,965)	0.0000
	Obs*R-squared	49.62156	Prob. Chi-Square(10)	0.0000
2020.1.20-2022.12.6	F-statistic	2.637424	Prob. F(10,676)	0.0037
	Obs*R-squared	25.79693	Prob. Chi-Square(10)	0.0040

3.2 Empirical tests

Daily CITIC Airline Index closing price data from January 4^{th}, 2016 to June 9^{th}, 2023 are collected from the

Wind database. January 4^{th}, 2016 - January 19^{th}, 2020 is defined as the period before the epidemic. January 20^{th}, 2020 - December 6^{th}, 2022 is defined as the period during the epidemic. Logarithmic return rate is calculated as is shown Table 5.

$$\mathrm{r} = \log \mathrm{p_t} - \log \mathrm{p_{t-1}} \tag{12}$$

The skewnesses of two period are less than 0, so the sequences are left skewed. The kurtoses are greater than 3, so the sequences have a spike feature. The p-values of the Jarque-Bera statistic are close to 0, which means that those data do not satisfy the normal distribution. To prevent the spurious regression phenomenon, the ADF test is performed to check whether the return series is smooth or not. The ADF test results are displayed in Table 6. The p-values of two series are much less than 0.05, so the original hypothesis of non-smoothness is rejected and the return series are smooth. In this paper, ARCH-LM is used to test the heteroskedasticity of model residuals to test whether there is a volatility agglomeration effect, the results of which are presented in Table 7. The p-values are less than 0.05, rejecting the original hypothesis which suggests that the series have ARCH effect at high order. Therefore, GARCH model can be built in both two period.

In order to determine the model order, AIC, SC and HQ are caculated. The GARCH-M(1,1), EGARCH(1,1,1) model are built because their values of AIC, SC, and HQ are the smallest. First, GARCH-M(1,1) is built to test the difference of return volatility of the period before and during the pandemic as is shown in Table 8. After the outbreak of the COVID-19, the ARCH coefficient and GARCH coefficient decreased, indicating that the volatility is less affected by the volatility of the previous period and long-term memory of the fluctuation decreased. However, the sum of α_1 and β_1 was still close to 1, indicating that volatility still persistent.

Next, EGARCH(1,1,1) is built to analyse leverage effect, the parameter of which is shown in Table 9. The p-value of γ_1 is significantly non-zero, indicating that airline stock market volatility has a "leverage effect". Before the COVID-19, γ_1 is greater than 0, indicating that the influence of positive information outweighs that of negative news. Positive news has an impact of 0.247, while the impact of bad news is 0.048. During the COVID-19, γ_1 is less than 0, indicating that the impact of negative news is stronger compared to positive news. The influence of positive news is -0.04, while the impact of bad information is 0.354.

Table 8. Parameter estimation results of GARCH before and during the COVID-19

	Before the COVID-19	During the COVID-19
w_0	-0.0000007	0.0000035
α_1	0.065165	0.038161
β_1	0.92695	0.901416

Table 9. Parameter estimation results of EGARCH before and during the COVID-19

	Before the new crown	During the New Crown
w_0	-0.250502	-8.161856
α_1	0.147455	0.157264
β_1	0.985672	0.170600
γ_1	0.099257	-0.196971

4 Limitations and prospects

This study is only restricted to China 's aviation stocks. In the future, the research can be extended to other countries. This paper only focuses on two major events. The impact of other major events of the COVID-19 can be researched on aviation stocks, such as lockdown in Wuhan and Shanghai. Due to the outbreak of the epidemic during the Chinese Spring Festival, a variety of factors influence the stock return. The analysis of other factors is not comprehensive enough. Next time, the result can be compared with the previous year 's data to consider other factors specifically. There are many major public health events around the world such as SARS and H1N1. This study only take COVID-19 as example. The impact of COVID-19 can be compared with other public health events in the future.

5 Conclusion

In summary, aviation stocks were negatively impacted by the COVID-19. Throughout the pandemic, unfavourable news exerted a more significant influence compared to positive news. Both the endurance and long-term recollection of the fluctuation diminished. The advent of the post-pandemic era brought about a notable beneficial effect on aviation stocks. Both impacts were relatively transient. This study bridges a gap of the impact of COVID-19 on aviation stocks. Nonetheless, there are still some limitations such as the limited number of events, lack of consideration of other factors' influence. In the future, further study will make up those limitations. Overall, these results offer a guideline for analysis under certain abnormal conditions.

References

1. S.S. Pere, J. of Trans. Geo. **86**, 102749-102749 (2020).
2. Y. Zhang, X. Liu, Fore. Eco. & Trade, **5**, 4 (2022).
3. S. Maneenop, S. Kotcharin S, J of Air Trans. Mana. **20**, 101920 (2020).
4. A. Bix, C. Bswa, of Air Trans. Mana. **89**, 626 (2023)
5. L. Wu, *Research on the impact of exchange rate fluctuations on stock returns of airline companies* (Guangdong University of Foreign Studies, 2021).
6. J. Zhan, R*esearch on the impact of public health emergencies on stock returns of Chinese airlines* (Fujian Normal University, 2021).
7. Thomas R. Cook, Johannes Matschke. China's Post-COVID Recovery: Implications and Risks. Economic Bulletin, Federal Reserve Bank of Kansas City, pages 1-4, 2023 May.
8. J. Guo, Z. Yang, Q. Zhong, et al., PLoS ONE 18, e0281950 (2023).
9. X. Chen, *Volatility of Chinese stock market under the shock of major public health emergencies*. (Liaoning University, 2022).
10. Z. Xia, *Research on the impact of the new crown epidemic on the inter-market spillover effect of the stock market* (Yunnan Normal University, 2022).
11. Y. Jin, Finan. Dev. Rev., **158(02)**, 65-78 (2023).