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Research on the Dynamic Fluctuations of AAL Stock Price with the impact of COVID-19

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ABSTRACT
The airline industry has come across severe hits since the outbreak of COVID-19, which is reflected by stock price fluctuations. This paper assesses the impact of global and regional epidemic situations on American Airline stock price. We build an ARMAX model, a VAR model, and an ARMA-GARCH model to analyze the changes of the stock price in value and volatility. This paper finds that epidemic outbreaks surprisingly have a positive impact on stock return and reduce its volatility, while the past of the stock price has a significant influence on its future value.

Keywords: *COVID-19, Stock price fluctuation, Airline industry, Stock volatility*

1. INTRODUCTION

At the beginning of 2020, the outbreak of COVID-19 started in China had interrupted the whole world. The increase of infections and death cases from the coronavirus was far beyond the market expectations, and soon it had spread around the world. The hit was so strong that there have been around 250 million confirmed cases and over 5 million deaths worldwide at the end of October 2021. Under such threat of getting infected and even dead, lifestyles of citizens were greatly changed all over the world: people had to work and communicate online, and production of all kinds of stuff has also stagnated for a while. Most companies were going through a bad time with a drastic decline in overall business, with few economic activities, and hoping for the coming of normal lives. However, some industries such as medicine, online education, and remote communication equipment were contrarily doing well, seeking their best opportunities during this particular period. Researches have shown that the damage of COVID-19 on the macroeconomy is even severer than that of the 2003 SARS epidemic. It will inevitably lead to the shrinking of global consumption, investment, service industries, and industrial production activities at least in short term. Specific industries such as infrastructure, transportation, and other fields will also suffer such damages.[1] The great impact of the COVID-19 has led to a sharp rise in uncertainty in the global market, which is soon be reflected in every stock market around the world.

The literature shows that a significant relationship exists between stock market returns and pandemic outbreaks, and the impact of the outbreaks is more likely to be a permanent one on the stock market.[2-3] Among the two kinds of most important data describing the development of the epidemic, stock markets reacted more proactively to the growth in a number of confirmed cases as compared to the growth in the number of deaths, and this response varies over time depending on the stage of the outbreak.[4] Surprisingly, even as infections continue to rise, equity markets may begin to rebound when the trajectory of the disease becomes less severe than initially anticipated.[5] All of these researches have revealed the complexity of the factors affecting market performance during the epidemic period, and also indicated the potential recovery capabilities of the market. These are parts of the reasons for doing further study in this field.

The transportation industry, which is the essential part of economic activities and the foundation of population mobility, has also received a major blow during this period. Very early from the pandemic outbreaks, governments around the world have prohibited cross-country transportation. Air fight continues to be canceled due to such policies and made a big hit on related companies. The employment situation of airlines began to deteriorate, and the market value of the airline business has shrunk since then.[6] Researches have found that airline stock returns decline more significantly than the market returns after three major COVID-19 announcements were made, and traders in western countries are more responsive to recent information than the rest of the world, indicating the even worse plight of the American airline industry.[7]

All these findings show the complexity of the analysis of the airline industry under the pandemic situation, which stimulates the further study of COVID-19 on the performance of the airline industry around the world. Based on this idea, this paper tries to look out for further corresponding relationships between the airline industries and epidemic situations, and take the stock American Airlines AAL as the case to make it.

This paper researches the AAL stock price fluctuation, which contains two properties of value and volatility. Firstly, the research focus on the value of the price, which determines the return of the stock and to some degree, the whole airline industry. The paper builds an ARMAX model to find out whether the COVID-19 has an influence on the stock price and how serious this impact is, comparing both the overall situation around the world and the American regional case. In the next part a VAR model is built, creating a system containing all three variables of AAL stock price, the number of American and World increased cases. The analysis of such complex interactions within this system is an improvement of what the paper has done in the first part. Additionally, this VAR system can also be used to make model-based predictions of the value of variables. Most importantly, the paper draws the impulse response graph to visualize these interactions in the system, which is a direct demonstration of the value of this model. In the final part of the paper, the research begins to focus on the volatility of the stock price, which indicates the risk of the stock price and the industry, and builds an ARMA-GARCH model. Based on the conditional heteroscedasticity found in the stock price series, the research lays great importance on the result of the GARCH part and draws conclusions based on the model performance.

2. RESEARCH DESIGN

2.1 Data source

Data of pandemic cases of both the United States and world in this paper is derived from Coronavirus Cases Online Research (CCOR) of Our World in Data Database.[8] CCOR has collected all kinds of important data about viruses including Cases, Hospitalization, Vaccinations, etc, and completed the COVID-19 dataset and visualize the data on confirmed cases and deaths from Johns Hopkins University (JHU). The JHU dashboard and dataset are maintained by a team at its Center for Systems Science and Engineering (CSSE). It has been publishing updates on confirmed cases and deaths for all countries since January 22, 2020. A feature on the JHU dashboard and dataset was published in The Lancet in early May 2020.[9] This has allowed millions of people across the world to track the course and evolution of the pandemic.

The price data of stock American Airline Group Inc. (AAL) is obtained by the Yahoo Finance website.[10] This is one of the most popular finance websites around the world and offers most of the financial data of all markets, especially in the U.S. area. Forming all historical data of AAL, the paper chooses the adjusted closing price, which amends the stock's closing price to reflect its value after accounting for any corporate actions such as stock splits, dividends, and rights offerings. In this case, the research could get an accurate estimation about how the market expectation of this company is fluctuate and is influenced by Covid-19 Cases.

This paper match the confirmed case data with the stock price data according to the date. Since stock price only changes during trading days, the research omits confirmed case data in non-trading days, and sort the remaining data by date and renumber it. When it comes to getting the logarithmic sequence of case data, the paper adds one to the original sequence in case of no newly confirmed cases in several days, which will not affect the final result of the research. In this research, Stata is most frequently used as the tool to solve the problems the research meets in further explorations.

2.2 Stock Return

During the research, this paper chooses logarithmic term as the stock return, which is calculated as:

$$return_t = \ln \frac{price_t}{price_{t-1}} = \ln price_t - \ln price_{t-1} \quad (1)$$

After being calculated and generated, the logarithmic stock return rate series is visualized in Figure 1.

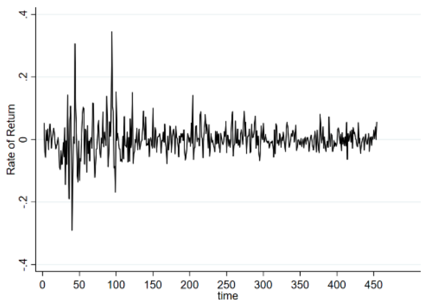

Figure 1 Rate of return

Note: The value of x-axis is the serial number of the trading days starting from January 22, 2020.

2.3 Unit Root Test

A Unit Root Test (Process) is used to check out whether a time series is stationary. Most quantificational analyses of time series are based on the premise that the series is stationary. As a result, before starting the research, the stationarity condition of data must be confirmed. If any series is not stationary, this paper needs to find possible methods to improve the results.

When doing Unit Root Test, it is usually assumed that the time series x_t can be written as:

$$x_t = c_t + \beta x_{t-1} + \sum_{i=1}^{p-1} \phi_i \Delta x_{t-i} + \varepsilon_t \quad (2)$$

In equation (2), c_t is the deterministic component such as trend or seasonal component. ε_t is a stationary error process. The coefficient β is used to find out the influence of the past on the present series. If the coefficient $\beta = 1$, which is also the null hypothesis of the test, it indicates that the series has a unit root and is not stationary. The alternative hypothesis is that $\beta < 1$, indicating the series under test is stationary.

Table 1 gives us the test results of raw data as well as the processed series:

Table 1 ADF-test result

Series Name	Z-Value	P-Value	Significance
Newly Confirmed Case in the U.S.	-3.154	0.0939	*
Logarithmic Newly Confirmed Case in the U.S.	-3.518	0.0375	**
Newly Confirmed Case of World	-3.337	0.0604	*
Logarithmic Newly Confirmed Case of world	-3.537	0.0356	**
AAL Stock Price	-3.535	0.0358	**
Logarithmic AAL Stock Price	-3.537	0.0356	**
Logarithmic AAL Stock Price Growth Rate	-14.430	0.0000	***

Note: The thresholds for z-value are - 3.982 (1%), - 3.422 (5%), - 3.130 (10%). ***, **, and * indicate the level of significance of 1%, 5%, and 10%, respectively.

It can be found from the result that the raw data series does not perform well in the stationarity test, the newly confirmed case in the U.S. and World series are not significantly stationary under 95% confidence intervals. However, when the logarithm series of the original data is taken, the improvement is very obvious: All logarithmic series of AAL stock price, newly confirmed cases in the U.S., and of the world are significantly stationary under 95% confidence intervals, and the stationarity condition of the logarithmic growth rate of AAL stock price can even be trusted under over 99% confidence intervals. Based on the results, this paper could build the following models with these stationary series.

2.4 ARMAX Model Specification

An ARMAX model is a combination of an Autoregressive (AR) process, a Moving Average (MA) process, and an X Distributed Lag (ADL) term.

An AR process is the same as $AR(p)$ model, under the assumption that the past of the time-series data plays an important role in determining its future. The parameter p of an AR model is the largest lag order of all lag terms considered in this model. An $AR(p)$ model can be written as:

$$y_t = \phi_0 + \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t \quad (3)$$

where ϕ_0 is a constant and y_t is the value of the series in period t, while ε_t is the present error term.

A MA process is a $MA(q)$ model predicting the future value depending linearly on the current and various past values of a stochastic term which indicates the error of predictions in the past periods. It can be written as:

$$y_t = c_0 + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} + \varepsilon_t \quad (4)$$

where c_0 is a constant and y_t is the present value of the series, while ε_t is the error term in period t.

An AR model and a MA model can form an ARMA model with both autoregressive and moving average processes. To build an ARMAX model, an X term needs to be added to the model, which is illustrated in an Autoregressive Distributed Lag (ADL) model. It can be written as:

$$y_t = \phi_0 + \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{k=0}^{l} \omega_k x_{t-k} + \varepsilon_t \quad (5)$$

where ϕ_0 is a constant and y_t is the value of the series in period t. ε_t is the error term. In this ADL model, $\phi_0 + \sum_{i=1}^{p} \varphi_i y_{t-i}$ can be seen as the AR process while $\sum_{k=0}^{l} \omega_k x_{t-k}$ can be considered as the X term of this model.

To fully consider the cause of AAL stock price fluctuation, this paper chooses to build an ARMAX model containing the impact from its past value, past error as well as the influence from the exogenous factors of the U.S. and World newly confirmed case. Its structure should be like this:

$$y_t = c_0 + \varepsilon_t + \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{k=0}^{l} \omega_k x_{t-k} \quad (6)$$

where y_t is the dependent variable, which is the logarithmic price of stock AAL in period t. c_0 is a constant. ε_t is the error term. x_{t-k} is the value of the X variable in period t-k. φ_t, θ_j, ω_k are corresponding coefficients. Using the lag operator applied to these components to simplify the equation, the paper defines the polynomial $\Phi(L), \Theta(L), \Omega(L)$ as

$$\Phi(L) = 1 - \varphi_1 L - \ldots - \varphi_p L^p,$$

$$\Theta(L) = c_0 L^{-1} + \theta_1 L + \ldots + \theta_q L^q,$$

$$\Omega(L) = \omega_0 + \omega_1 L + \ldots + \omega_l L^l$$

where $\Phi(L), \Theta(L), \Omega(L)$ stands for AR process, MA process, and XDL process. Then, it is straightforward to write (6) more compactly as:

$$\Phi(L) Y_t = \Theta(L) \varepsilon_t + \Omega(L) X_t + \varepsilon_t \quad (7)$$

2.5 VAR Model Specification

2.5.1 Build A VAR Model

Vector Autoregression Model (VAR) was first formally proposed by Sims in 1980.[8] It is a classic and pretty powerful statistical model used to explore the relationship between several time series as they change over time. On the premise that any variable is affected by the others in the group, instead of building a model for each variable, such as an ARMAX model, a VAR model puts these variables into a single system, doing a forecast to this multivariate time series as a whole.

To illustrate, when it comes to a VAR model with two variables (x_1, x_2) considering only one lag term $(p = 1)$, the system should be like:

$$x_{1,t} = c_{11} x_{1,t-1} + c_{12} x_{2,t-1} + \varepsilon_{x_1 t} \quad (8)$$

$$x_{2,t} = c_{21} x_{1,t-1} + c_{22} x_{2,t-1} + \varepsilon_{x_2 t} \quad (9)$$

It can be compactly written as a vector group like:

$$X_t = C \cdot X_{Lag} + E_t \quad (10)$$

where $X_t = \begin{bmatrix} x_{1,t} \\ x_{2,t} \end{bmatrix}, C = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}, X_{Lag} = \begin{bmatrix} x_{1,t-1} \\ x_{2,t-1} \end{bmatrix}, E = \begin{bmatrix} \varepsilon_{x_1 t} \\ \varepsilon_{x_2 t} \end{bmatrix}$.

In this case with three variables (stock price, world case, U.S. case), a $VAR(p)$ model can be written as:

$$y_t = \Gamma_0 + \Gamma_1 y_{t-1} + \ldots + \Gamma_p y_{t-p} + \varepsilon_t \quad (11)$$

where $y_t = \begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{bmatrix}, \Gamma_0 = \begin{bmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \end{bmatrix}, \varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}$,

$\Gamma_1 = \begin{bmatrix} \beta_{11} & \gamma_{11} & \lambda_{11} \\ \beta_{21} & \gamma_{21} & \lambda_{21} \\ \beta_{31} & \gamma_{31} & \lambda_{31} \end{bmatrix}, \ldots, \Gamma_p = \begin{bmatrix} \beta_{1p} & \gamma_{1p} & \lambda_{1p} \\ \beta_{2p} & \gamma_{2p} & \lambda_{2p} \\ \beta_{3p} & \gamma_{3p} & \lambda_{3p} \end{bmatrix}$.

In (11), y_t refers to the three response variables in this system. $\Gamma_0, \Gamma_1, \ldots, \Gamma_p$ are the coefficient matrix for corresponding terms. ε_t is the error term matrix in period t.

2.5.2 Impulse Response Graph of the VAR model

The estimates of VAR, 3*11 in total, in this case, are too many to be analyzed, so an impulse response graph is a useful tool for exploring the interaction within or between variables in the VAR system. A response graph creates an exogenous impulse and sees how the system response to it over time. Normally, a response effect can be calculated as:

$$\boldsymbol{\psi}_s = \frac{\partial \boldsymbol{y}_{t+s}}{\partial \boldsymbol{\varepsilon}_t'} \quad (12)$$

Equation (12) indicates that the response effect should be the change of $y_{i,t+s}$, the value of variable i in the timestamp $t + s$, when variable j increases by one unit in the disturbance term ε_{jt} at the timestamp t. If we describe (12) as a function of time interval s, it becomes the famous impulse response function (IRF).

The purpose of drawing an impulse response graph is to describe the development of variables in response to a shock in one or more variables. Since all variables in a VAR model are interdependent, individual coefficient estimates can only provide limited information about the system's response to shocks. As a result, Impulse Response (IR) is used to see a better picture of model's dynamic behavior, which allows us to track the transmission of a single shock within a complex and ever-changing system of equations. Normally, all impulse response results are drawn as graphs, which is a very useful tool in analyzing a VAR system.

2.6 ARMA-GARCH Model Specification

2.6.1 ARCH Model Specification

Before Engle introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model in 1982, economists did most of the researches under the assumption that the variance of a series is constant, which would not change much and obey the rule of the stochastic process.[9] However, for markets data in the real world where variance indicates the risk of assets, it is a norm that the variance fluctuates in different periods since the risk of markets is impossible to keep the same all the time. The ARCH model assumes that if a time series variance of the last period is high, possibly the variance of the next period is also high, which is an autoregressive logic similar to the AR model to forecast the variance in the future. Normally, an $ARCH(p)$ model can be written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \ldots + \alpha_p\varepsilon_{t-p}^2 \quad (13)$$

where σ_t is the forecast variance in period t. ε_t refers to the actual variance in period t. α_0 is constant.

2.6.2 GARCH Model Specification

In 1986 Bollerslev improved the ARCH model with the Generalized ARCH (GARCH) model by adding the GARCH term to the original ARCH model, making it the most fundamental and powerful model in time series analysis.[10] It is kind of like the same logic where an AR model turns into an ARMA model, and this process can reduce the number of coefficients to be estimated in the ARCH model. Take $GARCH(1,1)$ for an example to further explain. A $GARCH(1,1)$ with three terms can be written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \quad (14)$$

If keeping putting GARCH equation for $\sigma_{t-1}^2, \sigma_{t-2}^2, \ldots$ into the equation, (14) can finally be written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \ldots + \alpha_p\varepsilon_{t-p}^2 + \ldots \quad (15)$$

which is an $ARCH(\infty)$ model with infinite terms.

In more general cases, a $GARCH(p, q)$ model can be written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \ldots + \alpha_p\varepsilon_{t-p}^2 + \beta_1\sigma_{t-1}^2 + \ldots + \beta_q\sigma_{t-q}^2 \quad (16)$$

2.6.3 ARMA-GARCH Model Specification

Risk is almost the most important property of a market or an industry, considering that returns of markets are positively correlated with the risks they contain.[11-12] To focus on the risk, an ARMA-GRACH model is built to analyze the volatility of the AAL stock price. An ARMA-GARCH model is two equations of value and variance. Even though the value is also analyzed in the ARMA part, the GARCH part should be concentrated on to get the conclusion about the market risk.

3. EMPIRICAL RESULT

3.1 ARMAX Model Result

To build an ARMAX model, the paper first finds out the suitable AR and MA part of AAL stock price data.

Check the partial autocorrelation plot (PACF plot) of the series in Stata, the result is shown in Figure 2. The black rectangle is the benchmark to find out the statistically significant term in the AR model, from which it could be seen that the lag 1 and 3 terms of the original series may have a significant impact on the current data.

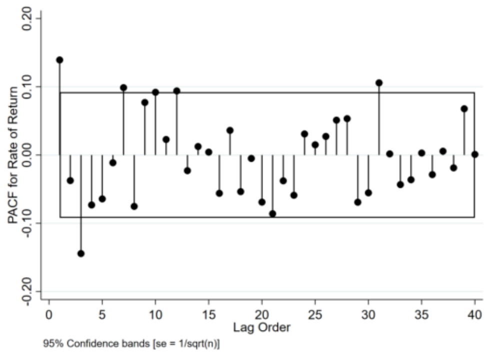

Figure 2 PACF Plot of AAL stock price data

To further confirm the result, the research use information criterion to find out the proper order p of the AR model. The result is shown in Table 2 which shows that feasible choices of the order of the AR model are 12, 3, and 1.

Autocorrelation Plot (ACF Plot) is used in this paper to determine the MA part of the series, a plot drawn by Stata is shown in Figure 3. It can be seen from the result that lag 1, 3, and 4 terms are a good choice for the moving average process.

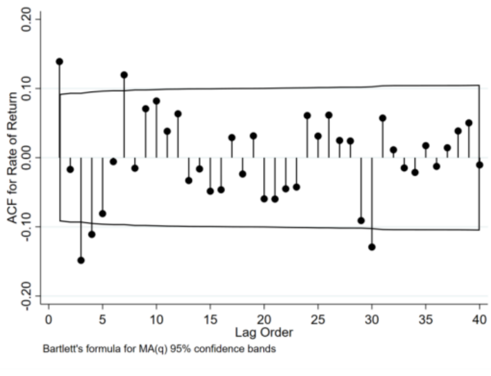

Figure 3. ACF Plot of AAL stock price data

Table 2 Order-selection result based on VARSOC

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	680.793				.002683	-3.08296	-3.0793	-3.07369
1	685.331	9.0762	1	0.003	.00264	-3.09901	-3.09169	-3.08046*
2	685.586	0.5089	1	0.476	.002649	-3.09563	-3.08465	-3.06781
3	690.353	9.5355	1	0.002	.002604	-3.11271	-3.09808*	-3.07563
4	691.607	2.5065	1	0.113	.002601	-3.11386	-3.09557	-3.0675

5	692.564	1.9155	1	0.166	.002602	-3.11367	-3.09173	-3.05804
6	692.575	0.0221	1	0.882	.002614	-3.10919	-3.08358	-3.04428
7	694.876	4.602	1	0.032	.002598	-3.11509	-3.08583	-3.04091
8	696.305	2.8564	1	0.091	.002593	-3.11703	-3.08411	-3.03358
9	697.593	2.5762	1	0.108	.00259	-3.11833	-3.08176	-3.02561
10	699.597	4.008	1	0.045	.002578	-3.12289	-3.08265	-3.02089
11	699.689	0.20248	1	0.653	.002589	-3.11881	-3.07492	-3.00755
12	701.666	3.9354*	1	0.047	.002577*	-3.1232*	-3.07565	-3.00266

After testing the several models built with different AR and MA terms, the paper finally finds the best ARMA term of $ARMA(3,1)$ which contains the AR terms of lag 1 and 3 as well as the MA term of lag 1. Consequently, this paper respectively adds X term which indicates the newly confirmed case of the U.S. or world to train the ARMAX with different lag orders to train the final ARMAX model. Table 3 gives us all results from different models.

Table 3 ARMAX model test results

	(1)	(2)	(3)	(4)	(5)	(6)
			Newly confirmed cases, U.S.			
T=0	.0018**	-.0077	-.0117			
	(.0008)	(.0068)	(.0067)			
T=-1		.0093	.0007			
		(.0066)	(.0107)			
T=-2			.0126			
			(.0084)			
			Newly confirmed cases, world			
T=0				.0032**	.0048	-.0049
				(.0013)	(.0071)	(.0114)
T=-1					-.0015	.0065
					(.0065)	(.0128)
T=-2						.0020
						(.0120)
			ARMA			
AR (-1)	.5034***	.5190***	.5647***	.5121***	.5120***	.5275***
	(.1082)	(.1047)	(.0970)	(.1085)	(.1089)	(.1065)
AR (-3)	-.1806***	-.1865***	-.1964***	-.1837***	-.1838***	-.1883***
	(.0290)	(.0295)	(.0320)	(.0297)	(.0300)	(.0309)
MA (-1)	-.4229***	-.4480***	-.5081***	-.4361***	-.4360***	-.4534***
	(.1207)	(.1174)	(.1100)	(.1215)	(.1221)	(.1200)
Constant	-.0185***	-.0174***	-.0171***	-.0406***	-.0413***	-.0447***
	(.0076)	(.0075)	(.0079)	(.0143)	(.0153)	(.0163)

Note: T indicates the lag order. In the two rows of each lag, the first one indicates the estimated coefficient of the term, and the second is the standard error of the estimated result. ***, **, and * indicate the level of significance of 1%, 5%, and 10%, respectively.

All coefficients of $ARMA(3,1)$ part of models show great significance, while only lag one term of X of U.S. and World case show significant impact on AAL stock price.

The first column of estimates shows that the number of the newly confirmed case of COVID-19 in the United States is significantly positively correlated with the price of AAL stocks, which is a little bit counter-intuitive. Specifically, For every 1% increase in the number of confirmed cases in the U.S., the price would increase by 0.18%. Then, the paper put more lag terms of the U.S. case in the model step by step, the relationship between AAL stock price and the U.S. newly confirmed cases begins to change. The result can be seen in column (3) that newly confirmed case becomes negatively correlated with the stock price at a degree of significance of 10%, indicating that the domestic epidemic outbreak in the United States has a negative impact on the airline stock return.

The result of the world case is similar to the U.S. case. Column (4) shows that for every 1% increase in the world's newly confirmed case number, the AAL stock price respond by moving up by 0.32%, which is also a surprising positive correlation. But after considering the lag terms, though still showing a reversal of correlation relationship, the final estimated coefficient result in column (6) shows no significance, which may indicate that COVID-19 of the world may have little impact on stock price in the long run.

3.2 VAR Model Result

3.2.1 VAR Order Selection

In this part, the paper put three stationary series: logarithmic stock price, logarithmic newly increased confirmed case in U.S. and world, into our Vector Autoregression system. Firstly, different VARSOC selection-order criteria in Stata are used to find out the suitable order p of this $VAR(p)$ model. The result is shown in Table 4 indicating that a VAR with 11 orders can be taken into account.

Table 4 Order-selection result based on VARSOC

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1307.82				.075597	5.93129	5.94224	5.95906
1	616.95	3849.5	9	0.000	.000013	-2.73733	-2.69352	-2.62625
2	661.495	89.09	9	0.000	.000011	-2.89817	-2.88215	-2.70378
3	675.132	27.274	9	0.001	.000011	-2.91915	-2.80962	-2.64146
4	710.312	70.359	9	0.000	9.6e-06	-3.03761	-2.89522	-2.67661
5	716.949	13.274	9	0.151	9.7e-06	-3.02692	-2.85167	-2.58261
6	769..703	105.51	9	0.000	8.0e-06	-3.2249	-3.0168	-2.69729
7	796.925	54.444	9	0.000	7.4e-06	-3.30735	-3.06639	-2.69643
8	808.723	23.596	9	0.005	7.3e-06	-3.32001	-3.04619	-2.62579
9	823.992	30.538	9	0.000	7.1e-06	-3.34838	-3.0417	-2.57085
10	861.192	74.399	9	0.000	6.2e-06	-3.47598	-3.13644	-2.61514
11	1001.84	281.1*	9	0.000	3.4e-06*	-4.07122*	-3.69882*	-312707*
12	1009.08	14.678	9	0.100	3.5e-06	-4.0637	-3.65845	-3.03625

3.2.2 Stability Condition of VAR Estimates

After building $VAR(11)$ model, this paper uses a code-named varstable tool in Stata to check the eigenvalue stability condition after estimating the parameters of a vector autoregression, which would draw a unit circle to visualize the result. If all dots indicating the eigenvalues lie inside the unit circle, it could be told that the VAR estimates are stable. Figure 4 gives us the plot result, which tells that the stability condition of this VAR system is satisfied.

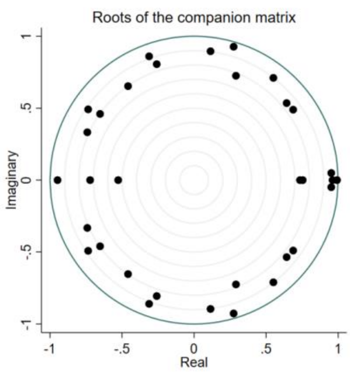

Figure 4 Stability Condition of VAR Estimates

3.2.3 Forecast of Price

With the VAR model result, this paper does forecast AAL stock price in the nearby future, the result is shown in Figure 5. According to the model estimation results, AAL stock price has a downward trend in the short term, but the impact is limited.

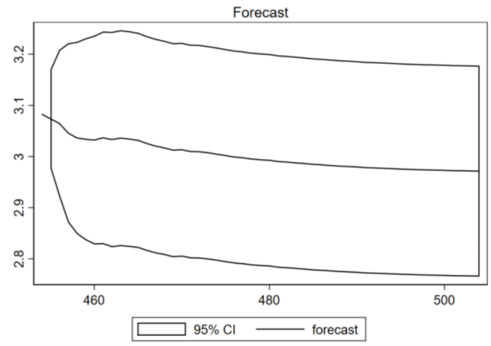

Figure 5 Impulse from AAL Stock Price

3.2.4 Impulse Response Graph of the VAR model

Figure 6 and 7 show the impulse response results of variable AAL stock price. It can be seen from the figures that one unit of the newly increased confirmed case of the U.S. would cause a short-term decline in AAL stock price, but the increase of cases worldwide leads to a short-term upward movement. In the long run, the impact of repress on stock price from U.S. case gradually dies down and even reverses at around 18 lags (18 trading days later).

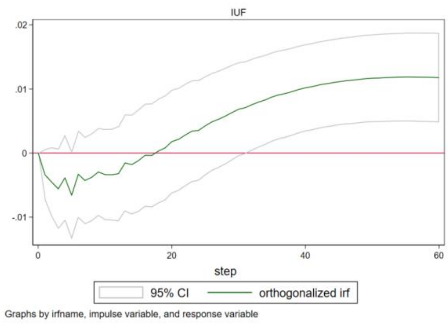

Figure 6 Impulse from the U.S. increased cases

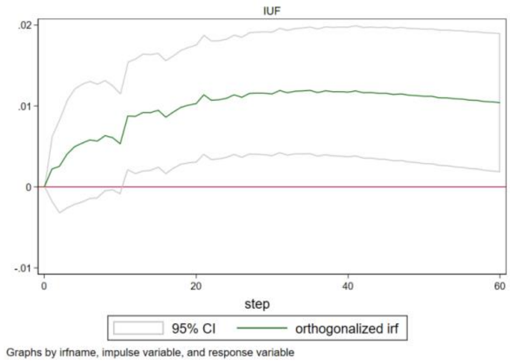

Figure 7 Impulse from world increased cases

3.3 ARMA-GARCH Model Result

3.3.1 Conditional Heteroscedasticity

A GARCH term should be considered when conditional heteroscedasticity exists in the original sequence. As a result, before building an ARMA-GARCH model, the variance condition of the stock price series needs to be checked. From the previous plot of the return rate series in figure 1, it could be told that the return rate series has conditional heteroscedasticity.

3.3.2 ARMA-GARCH Model Result

Based on what has been done in building the ARMAX model, this paper uses an $ARMA(3,1) - GARCH(1,1)$ model with exogenous lag terms of U.S. or World case to train the model. As the former discussion, this paper is more concerned about the variance equation in the GARCH part, getting focused to find out whether the severity of the COVID-19 situation has led to the volatility change of the stock is shown in Table 5.

Table 5 ARMA-GARCH model result: The Variance equation with multiplicative heteroskedasticity specification

	(1)	(2)	(3)	(4)	(5)	(6)
			Newly confirmed cases, U.S.			
T=0	-.1620**	1.8729***	-.9306			
	.0641	.4473	2.6517			
T=-1		-1.9300***	2.9467			
		.3574	3.2529			
T=-2			-2.0322***			
			.5487			
			Newly confirmed cases, world			
T=0				-.5896***	-1.0094***	-.8049**
				.0438	.3149	.3295
T=-1					.4526	.0653
					.2953	.3743
T=-2						.1634

						.2610
ARCH	.0719**	.0268*	.0321*	.1886***	.2456***	.2256***
	.0287	.0161	.0180	.0669	.0827	.0881
GARCH	.9029***	.9483***	.9425***	-.1248***	-.0129	-.0483
	.0300	.0177	.0186	.0466	.8273	.1414
Constant	-8.3880***	-10.1527***	-10.6613***	1.0113**	.4352	.7396
	.6751	1.2656	2.7216	.5168	.5898	.6133

Note: T indicates the lag order. In the two rows of each lag, the first one indicates the estimated coefficient of the term, and the second is the standard error of the estimated result. ***, **, and * indicate the level of significance of 1%, 5%, and 10%, respectively.

Based on the result of columns (3) and (6), it can be told that surprisingly, the newly confirmed case in the U.S. and worldwide didn't increase the volatility of the stock price of AAL. In the short run, the result even shows that the epidemic increase may repress the fluctuation of stock price, which is really out of expectation.

4. DISCUSSION

This article finds that AAL stock price is significantly influenced by its past. Apart from that, surprisingly in the short run, the newly confirmed epidemic case significantly positively correlated with the stock price. In the long run, however, the relationships have reversed, but epidemic cases become no longer a significant predictor of the future stock price.

Even the forecast of the VAR model shows the stock price will go downward in a short period, it would more likely be the impact from its past but not the pandemic situation since the result of the VAR model indicates that an impulse from the newly confirmed case would cause a permanent increase in the logarithmic AAL stock return. The response of impulse from the world newly confirmed case is an immediate increase and steady upward trend in the stock price, and it will make a converge to keep stable at around 20 lags later. The impulse from the U.S. may firstly lead to a drop in price in the short run. However, after around 18 trading days, the cumulative response will become positive and continue to grow upward significantly. Finally, it will become steady at the period of around 40 lags.

The ARMA-GARCH model finds that in the short term, the newly confirmed U.S. and world case would surprisingly repress the volatility of the stock price. In the long run, case increases still would not trigger the fluctuation of the price. Compared to the world case, newly confirmed cases within the U.S. have a more significant impact on the volatility of the stock price. The effect of repression may be formed when price plummet caused by the pandemic outbreak has shrunk the AAL stock-trading market. With lower transaction volume, the price volatility would become less, which just coincides with the research done by G Chen, M Firth, and OM Rui in 2001.[13] Additionally, the risk of the AAL stock market may be completely or even overly released when the first round of epidemic outbreaks hit the global market.

Further research can be carried out from two aspects: First, as the paper has done before, with a GARCH term, the former ARMAX model can be improved with the same GARCH term to make a more precise analysis of the stock price. Second, since the influence of the past of the stock price is more significant than pandemic situations, further research could add in other exogenous variables to find out a powerful indicator such as inflation rate, which also had great changes during the COVID-19 period.

5. CONCLUSION

COVID-19 has made a big change to the global economy. During this period, different industries react differently to epidemic outbreaks. This paper researches how global and regional newly confirmed cases influence the stock market. This paper focuses on the stock return based on the premise considering the impact from its historical values and does further research on its volatility reaction. The research draws counter-intuitive results showing that the outbreaks show a positive correlation with the stock return and shrink the volatility of the stock which is normally considered as an indicator of market risk.

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