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Overflow Effect of COVID-19 Pandemic: Evidence from China and US Based on Time Series Model

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Abstract: It is widely acknowledged that COVID-19 which outbroke at the end of 2019 has brought great change to people's daily lives and has had a huge impact on the global market. In order to study the intercorrelation of the pandemic in China and the United States and each other's economic markets, this paper uses the VAR model and the ARMA-GARCH model. This paper mainly utilizes the data from February 03, 2020, to December 15, 2022, to study the effect of the pandemic in China on the U.S. market and the effect of the pandemic in the United States on the Chinese market. This study discovers that the increase in the pandemic in the U.S. is insignificant in relation to the Chinese market while the pandemic in China will affect the U.S. stock market. This paper reminds people of considering the consequence of the pandemic in a wider context and provides new aspects for future researchers. The results of this study suggest investors consider things more rationally before making a decision and suggest governments make wiser plans to limit the irrational behavior of investors and prevent the market from fluctuating when similar cases happened in the future.

Keywords: China, US, COVID-19, stock returns, time series model

1. Introduction

People from all over the world have been affected negatively by the epidemic and the lockdown since COVID-19 began in 2019. First of all, the lockdown of many countries, especially the lockdown of China, has imposed huge negative consequences on the global economy. For example, when the epidemic situation in Shanghai was extremely serious. Shanghai, China's financial center which has conducted many cross-border transactions, has been locked down for months in 2022. This lockdown has led to a significant increase in air and freight rates and delays in ports and has laid huge pressure on global trade [1].

Due to the stress and uncertainty brought on by the pandemic, people's emotions and behavior have changed a lot. Since the outbreak in 2019, due to people's unfamiliarity and unknown of COVID-19, panic has spread rapidly among people. For one thing, people feel worried and afraid of getting infected and losing their lives because of it. For another, people's lives and work are seriously affected due to the lockdown. For example, many people around the world decided to stock up on some daily necessities, like napkins and food. In China, everyone is required to wear a mask when going out. Moreover, fears and unknowns about COVID-19 drive them to do some irrational behaviors. For example, when people in China hear rumors that "Lianhua Qingwen will prevent COVID-19", they rush to the drugstores to buy Lianhua Qingwen capsules.

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As the most developed countries in the economy in the world, China and the United States have always played important roles in the global economy. In the context of the epidemic situation, many existing documents are about the impact of a country's epidemic situation on its own development or the impact of the global epidemic situation on a country's economy. But there is a gap in the existing research which is the influence of the two countries' pandemic on each other's stock markets. This paper can fill up this blank on some levels. This paper studies the effect of the U.S. pandemic on the Chinese stock market and the effect of the Chinese pandemic on the U.S. stock market.

The remaning parts of this paper will be arranged as follows: The second section of this article introduces the research design like the data source, and the basic concept of the Augmented Dickey–Fuller (ADF) Unit Root Test, Vector Autoregression (VAR) Model, and ARMA-GARCH Model. The third section uses the VAR Model and ARMA-GARCH Model to conduct empirical analysis. Finally, sections four and five talk about the discussion and conclusion.

2. Literature Review

2.1. Studies Related to United States' Stock Market

More than 100,000 people worldwide have been impacted by COVID-19, which has undoubtedly had an influence on the real economy. As a consequence, trade, tourism, and the transportation industry have all suffered. The pandemic also leads to the local food shortage [2]. COVID-19 is spreading particularly fast in the United States, and therefore has brought a huge impact on the U.S. stock market. This study empirically investigates how the pandemic affects U.S. stock markets and explores different sources that affect financial volatility. Ordinary Least Squares (OLS) regression is tested in this study and researchers investigate how coronivarus affects on financial volatility. In specific, they estimate two models and conduct two types of analysis to study the role of the announcements of the new cases and the effect of the fatality ratio. According to both results, researchers discovered that COVID-19 significantly reduces market volatility [3]. Additionally, the global level has a greater influence on the S&P 500 realized volatility than the US fatality ratio does. The results of this study show that (i) the financial volatility is made worse by the new infection cases that have been reported both globally and in the US. (ii) The fatality ratio significantly affects volatility. (iii) The impact of COVID-19 data reported globally is greater than the impact caused by data released in the US. (iv) EPU has a negligible effect on financial volatility during COVID-19's pandemic phase.

2.2. Studies Related to the Effect of the Pandemic on the Chinese Stock Market

Coronavirus has brought a significant negative impact on the global economy. Many researchers have noted plummets during the pandemic. For instance, circuit breakers occurred to the American stock market two times in a week. The efficient market theory holds the view that the substantial economic loss brought by the pandemic is responsible for the volatility. If that is the case, Hubei Province enterprises' stock returns should perform substantially worse than average because Hubei is the center of the epidemic. However, the study shows that the stock returns of Hubei companies are consistent with the market. Pharmaceutical stock anomalous returns did not endure as long [4].

In order to investigate how sentiment affected stock market volatility during the outbreak, this study evaluates two hypotheses. The first hypothesis tested is that the pandemic gives rise to strong negative sentiments, like panic and anxiety. The second one is COVID-19 results in yields of the associated stocks lower than usual.

According to the descriptive statistics, the pandemic has a detrimental impact on both stock returns and investor sentiment. In the meantime, the outbreak caused a decline in the yield on the Chinese stock market and an increase in volatility. The results about pharmaceutical stocks imply that the pandemic has a significant positive impact on the stock prices of pharmaceutical manufacturers. The average CAR of the entire market was impacted by pharmaceutical companies by 23.12%, which skewed the results overall . The pandemic is a long-term issue and has a great positive impact on the stock price since the cumulative anomalous return of the entire market is negative and declines in the post-event window [4]. The results of the study show that the difference between the cumulative abnormal return of stocks belonging and not belonging to firms in the pharmaceutical industry after the pandemic is greater than in the period before the outbreak of COVID-19. This supports the view that it is the epidemic who has caused this kind of industrial differences and that the investors in this market are irrational [4].

2.3. Review

Overall, there is already some research exploring the effect of the pandemic on the stock market of different countries. However, few researchers study the effect of the pandemic of the two countries on each other's stock markets. Hopefully, this paper can fill this gap and provides a new angle for future researchers.

3. Research Design

3.1. Data Source

This study collects all the data from a prevalent search engine--Choice financial terminal. Choice Financial Terminal is a financial terminal that covers the stock, fund, bond, index, commodity, money market [5]. This paper uses daily closing stock prices of Nasdaq and SSEC and daily total confirmed cases in China and the United States from February 03, 2020, to December 15, 2022. Since the purpose of this paper is to discuss the effect of the daily new confirmed cases in China on the American stock market and the effect of the daily new confirmed cases in the U.S. on the Chinese stock market, the data analyzed in this paper should be the daily new confirmed cases in both countries. Therefore, the data collected from the Choice financial terminal is processed in Excel. To calculate the daily growth in US and Chinese new cases, the author uses today's total confirmed cases minus the total confirmed cases on the previous day. Also, to obtain the Nasdaq and SSEC stock returns, this paper divides the difference between two days' closing stock prices collected from the Choice Finance Terminal by the one on the previous day. Then, this paper transforms the data into a logarithmic scale by using the formula, which is more convenient to analyze. To be clear, since there are some missing data on the website of the Choice financial terminal, the study assumes the daily new confirmed cases of two countries are zero on those days. The data collected from the Choice Finance Terminal and processed in Excel serves as a strong data source and data basis for the following empirical analysis. Stata, an extremely useful tool, was used to analyze those data and build all the models.

3.2. ADF Unit Root Test

Before starting to build models, testing whether the data are stationary is an important step [6]. Testing the data found from the Choice financial terminal in Stata lead to the ADF test results in Table 1. Table 1 shows that the p-value for daily new confirmed cases in China equals 0.0013 and the p-values for Nasdaq, SSEC, and the daily new confirmed cases in the United States all equal zero. All of these p-values are less than 0.01, which means they are statistically significant. The testing results in Table 1 serve as strong evidence to reject that the variables have a unit root. Therefore, all data are stationary and the subsequent models built in this paper are feasible.

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Table 1: ADF test.

Variables		t-statistic	p-value
Raw index			
	Nasdaq	-0.882	0.9581
	SSEC	-2.342	0.4111
Yield			
	Nasdaq	-18.076	0.0000***
	SSEC	-17.443	0.0000***
New confirmed cases			
	CN	-4.539	0.0013***
	US	-12.000	0.0000***

3.3. VAR Model

The VAR model is initially used for the study of linear stochastic difference equations [7] and research on the autoregressive nature used for Tinbergen's model [8].

VAR, a stochastic process model, can be applied to capture the relationship between multiple variables as they change over time [9]. VAR models are commonly used to estimate the dynamic relationships of jointly endogenous variables. It is achieved by autoregression of all current period variables in the model on several period lags of all variables.

It is acknowledged that the coronavirus has had a huge impact on the global market. Many cross-border transactions are hindered by the lockdown. However, little research contributes to the relationship between the Chinese market and the daily new confirmed cases in the United States and the U.S. market and the daily new confirmed cases in China. In this study, there are four separate time series variables: the closing prices of Nasdaq and SSEC and the daily new confirmed cases in China and the United States. These variables are denoted by $x_{t,1}, x_{t,2}, x_{t,3},$ and $x_{t,4}$. Based on the four time series variables, VAR (4) model was built.

$$x_{t,1} = \alpha_1 + \phi_{11}x_{t-1,1} + \cdots + \phi_{1p}x_{t-p,1} + \beta_{11}x_{t-1,2} + \cdots + \beta_{1p}x_{t-p,2} + \delta_{11}x_{t-1,3} + \cdots + \delta_{1p}x_{t-p,3} + \gamma_{11}x_{t-1,4} + \cdots + \gamma_{1p}x_{t-p,4} + e_{1t} \tag{1}$$

$$x_{t,2} = \alpha_2 + \phi_{21}x_{t-1,1} + \cdots + \phi_{2p}x_{t-p,1} + \beta_{21}x_{t-1,2} + \cdots + \beta_{2p}x_{t-p,2} + \delta_{21}x_{t-1,3} + \cdots + \delta_{2p}x_{t-p,3} + \gamma_{21}x_{t-1,4} + \cdots + \gamma_{2p}x_{t-p,4} + e_{2t} \tag{2}$$

$$x_{t,3} = \alpha_3 + \phi_{31}x_{t-1,1} + \cdots + \phi_{3p}x_{t-p,1} + \beta_{31}x_{t-1,2} + \cdots + \beta_{3p}x_{t-p,2} + \delta_{31}x_{t-1,3} + \cdots + \delta_{3p}x_{t-p,3} + \gamma_{31}x_{t-1,4} + \cdots + \gamma_{3p}x_{t-p,4} + e_{3t} \tag{3}$$

$$x_{t,1} = \alpha_4 + \phi_{41}x_{t-1,1} + \cdots + \phi_{4p}x_{t-p,1} + \beta_{41}x_{t-1,2} + \cdots + \beta_{4p}x_{t-p,2} + \delta_{41}x_{t-1,3} + \cdots + \delta_{4p}x_{t-p,3} + \gamma_{41}x_{t-1,4} + \cdots + \gamma_{4p}x_{t-p,4} + e_{4t} \tag{4}$$

The equations (1), (2), (3), and (4) above are for Nasdaq and SSEC stock return and the daily new confirmed cases in China and the U.S. respectively. To clarify, in equation (1), $\alpha_1 + \phi_{11}x_{t-1,1} + \cdots + \phi_{1p}x_{t-p,1}$ and $\beta_{11}x_{t-1,2} + \cdots + \beta_{1p}x_{t-p,2}$ represent the linear functions of past lags of Nasdaq stock return and SSEC stock return, while $\delta_{11}x_{t-1,3} + \cdots + \delta_{1p}x_{t-p,3}$ and $\gamma_{11}x_{t-1,4} + \cdots + \gamma_{1p}x_{t-p,4}$ represent past lags of daily new confirmed cases in the U.S. and China, and $e1t$ is the error term. As a result, VAR (4) model in this study is built on the historical values for the four separate time series variables. Similarly, the other three equations have similar structures, but each equation has different variables and coefficients.

3.4. ARMA-GARCH-X Model

The ARMA-GARCH model can be used to evaluate both the return and volatility of the Nasdaq and SSEC stock. In this paper, ARMA-GARCH model is divided into two sections: ARMA and GARCH.

$$y_{t1} = \phi_0 + \sum_{i=1}^{p} \phi_i \, y_{t1-i} + \alpha_i - \sum_{i=1}^{q} \phi_i \, \alpha_{t1-i} \tag{5}$$

$$y_{t2} = \phi_0 + \sum_{i=1}^{p} \phi_i \, y_{t2-i} + \alpha_i - \sum_{i=1}^{q} \phi_i \, \alpha_{t2-i} \tag{6}$$

The equation (5) and (6) show the general expression of the ARMA model. $\phi_0 + \sum_{i=1}^{p} \phi_i \, y_{t-i}$ in both equations represent the AR(p), while $\alpha_i - \sum_{i=1}^{q} \phi_i \, \alpha_{t-i}$ represent MA(q). AR(p) estimates future value applying past SSEC or Nasdaq stock returns from February 2020 to December 2022, whilst MA(q) forecasts using an error term.

The GARCH model is derived from the ARCH model, with the addition of autoregression of σ^2. This paper builds GARCH (1,1). The first "1" in the bracket represents one autoregressive lag, and the second "1" represents one moving average lag [4]. The reason why this study selects GARCH (1,1) is: GARCH can examine the influence of exogenous variables on volatility in the variance equation. Therefore, GARCH (1,1) was built:

$$\sigma_t{}^2 = \alpha_{0,1} + \alpha_1 \varepsilon_{t-1}{}^2 + \beta_t m_t + \gamma_1 \sigma_{t-1}{}^2 \tag{7}$$

In equation (7), $\alpha_1 \varepsilon_{t-1}{}^2$ is the ARCH part, and $\gamma_1 \sigma_{t-1}{}^2$ is the GARCH part, and the additional term $\beta_t m_t$ other than the generalized formula represents confirmed cases that acted as an extra explanatory variable in the model.

4. Empirical Results and Analysis

4.1. Order of VAR Model

The first significant empirical analysis step is to find out the optimal lag order for a VAR model. The LR value and all the other statistical criterions of each lag are assessed, but eventually, this paper finds out the optimal lag order according to the LR value.

$$LR = -2(\log L_k - \log L_{k+1}) \tag{8}$$

When the LR statistic is less than the critical value, the lag order of the VAR model is considered appropriate. In Table 2, a sign (*) is used to signify the desired lag order.

Table 2: VAR model identification.

Lag	LL	LR	p	FPE	AIC	HQIC	SBIC
0	531.597			2.0e-06	-1.7854	-1.7738	-1.7557
1	1290.61	1518	0.000	1.6e-07	-4.2998	-4.2421	-4.1515
2	1347.19	113.17	0.000	1.4e-07	-4.4372	-4.3332	-4.1702*
3	1370.33	46.272	0.000	1.4e-07	-4.4613	-4.3111	-4.0758
4	1390.97	41.28	0.001	1.3e-07	-4.4770	-4.2806	-3.9728
5	1480.42	178.9	0.000	1.0e-07*	-4.7256*	-4.483*	-4.1028
6	1494.19	27.553*	0.036	1.0e-07	-4.7180	-4.4292	-3.9766

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Table 2: (continued).

7	1503.23	18.073	0.320	1.1e-07	-4.6945	-4.3594	-3.8344
8	1509.74	13.021	0.671	1.1e-07	-4.6624	-4.2811	-3.6837
9	1519.27	19.06	0.266	1.1e-07	-4.6405	-4.2130	-3.5432
10	1528.82	19.1	0.263	1.2e-07	-4.6186	-4.1450	-3.4027
11	1537.3	16.958	0.388	1.2e-07	-4.5932	-4.0733	-3.2586
12	1543.44	12.281	0.724	1.2e-07	-4.5598	-3.9937	-3.1066

As shown in Table 2, lags 2, 5, and 6 all have the sign. However, according to the LR statistic, the most optimal lag order for the VAR model should be 6.

Following finding the optimal lag order for the VAR model, there is another important step which is to examine whether the VAR model is stationary. The reason why the examination is important is that only the OLS estimation of the VAR model composed of stationary variables can lead to consistent estimation parameters. If the VAR model is non-stationary, the impulse-response function will not converge to zero. The applicability of the VAR model was examined by the unit root test. The results in Figure 1 reveal that all of the roots are clearly within the circle in Figure 1, which implies that VAR (6) is a stable model.

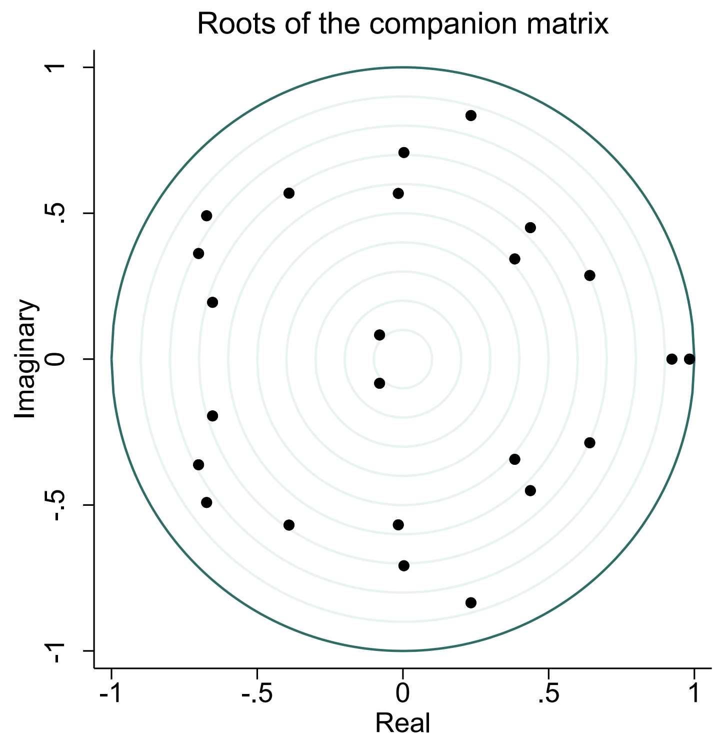
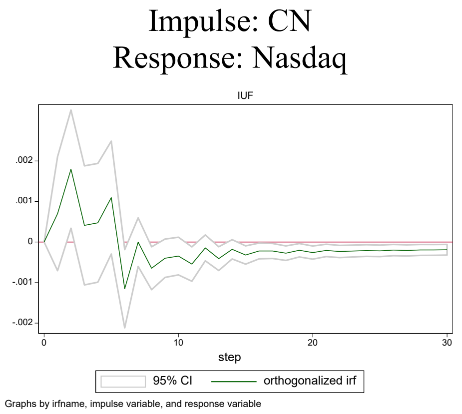


Figure 1: VAR stability.(Photo credit: Original)

4.2. Impulse Response

This paper studies how SSEC stock returns respond to the daily new cases in the U.S. and how Nasdaq stock returns respond to daily new cases in China.



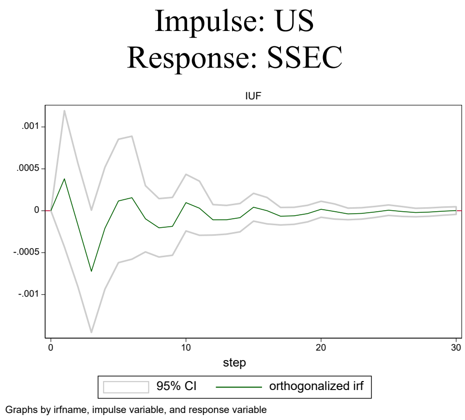


Figure 2: Impulse and response.(Photo credit: Original)

From a fundamental point of view, the outbreak of COVID-19 in 2019 led to turmoil in the global financial markets. No matter whether in China, the U.S., or Europe, investors panicked in the short term after the rapid spread of COVID-19, and the risk aversion of capital led to a massive "flight to safety" from financial markets, which in turn led to a precipitous decline in financial market indices. For instance, compared to January 5, 2020, stocks in Asia, Europe, and the United States in March 2020 all decreased by roughly 20% to 25%, 40%, and 40%, respectively [10].

According to the US stock market index US30, the stock was reduced by almost half on March 20, 2020, causing panic until March 25. The stock made an outstanding recovery in such a short amount of time, rising nearly 20% above the low. Despite a deeper understanding of the COVID-19 epidemic, more long-term information is needed to determine whether or not the investors' behavior will return to normal, or whether the impact will be long-term.

After the COVID-19 outbreak becomes normalized in China and globally in mid-2020, equity markets in both China and the U.S. begin to climb all the way up.

In the long run, it is worth exploring whether the epidemic in China and the U.S. have an impact on each other's stock markets as awareness of COVID-19 deepens and whether behavior returns to rationality.

The impulse response function, with the impulse variable being the addition of the Chinese daily logarithm and the response variable being the Nasdaq return, is depicted in Figure 2's left panel. It can be found that a 1% increase in the amounts of new confirmations in China in period t=0 has a positive net effect on Nasdaq returns. The effect on S&P 500 returns is positive from period t=1 to t=5 and turns negative thereafter.

This paper suggests that this is related to the behavior of Chinese investors. There is a general academic consensus that Chinese investors' investment behavior is easily dominated by emotions and lacks rationality. In the long run, the increase in the number of new confirmed cases in China still causes Chinese investors to panic and shift their capital to other markets. This suggests that the outbreak of COVID-19 has a long-term impact on Chinese investors' behavior.

The right panel in Figure 2 shows the impulse response function with the impulse variable being the daily new confirmed diagnoses in the U.S. and the response variable being the SSE index return. It can be observed that an increase in the number of new confirmed diagnoses in the U.S. does not have a similar effect on the SSE index return, but only causes its return to oscillate around the value of zero.

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4.3. Order of ARMA Model

To find out the order of ARMA Model, this study uses PACF and ACF to discover the lag orders for AR(p) and MA(q). In the Figure 3, for SSEC stock returns, there are no lags beyond the critical value, and therefore this study did not use the AR(p) and MA (q) in the model. Figure 3 also shows that for Nasdaq stock returns, in both PACF and ACF, the first lag and the second lag beyond the critical values is 1 and 2 for both PACF and ACF plots. Hence, this study uses AR(1,2) and MA(1,2) in the following steps.

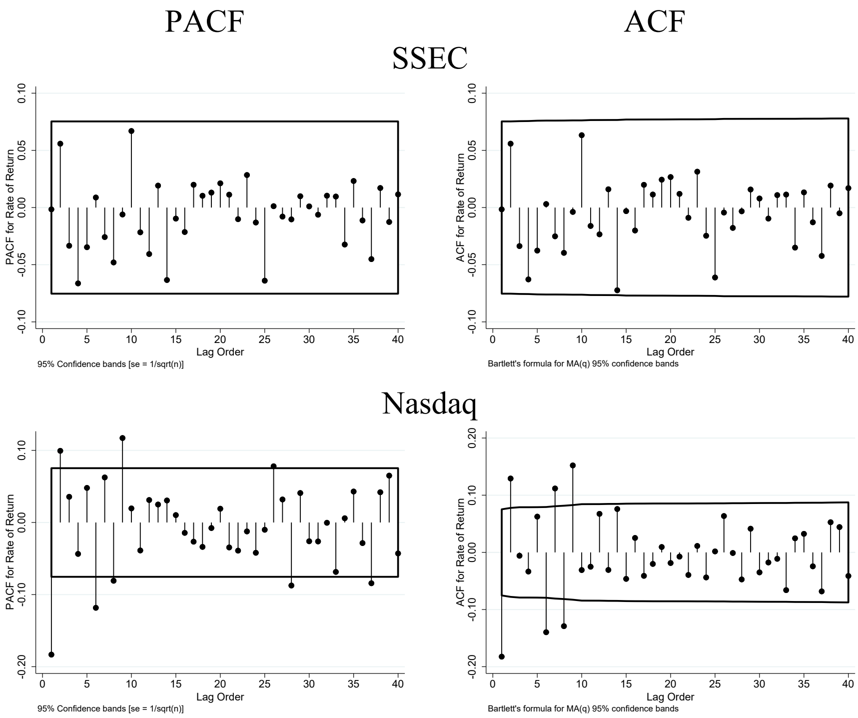

Figure 3: PACF and ACF.(Photo credit: Original)

4.4. ARMA-GARCH Estimation Results

According to the estimation results of Table 3, the Nasdaq and SSEC stock returns Both ARCH and GARCH terms are significant at the 1% level, i.e., there is conditional heteroskedasticity and GARCH modeling can be performed.

From the estimates of the external explanatory variables, the daily new confirmed cases in China have increased by 1% and the Nasdaq volatility has increased by 0.3736 units, with the coefficient significant at the 1% level. However, the daily new confirmed cases in the U.S. do not have a significant impact on the fluctuation of SSEC.

Table 3: ARMA-GARCH estimation results.

	(1)			(2)		
	Nasdaq			SSEC		
	Coef.	Std. Err.	P>|z|	Coef.	Std. Err.	P>|z|

Table 3: (continued).

New confirmed cases						
CN	.3736	.0952	0.000			
US				-.0284	.0487	0.560
ARCH, L1	.1185	.0245	0.000	.0705	.0273	0.010
GARCH, L1	.8519	.0257	0.000	.8720	.0494	0.000
Constant	-13.3031	.5872	0.000	-11.6499	.6992	0.000

5. Discussion

Compared to the existing literature, this paper also uses VAR and ARMA-GARCH models to conduct the study. However, with the existing literature mainly exploring the impact of COVID-19 in one country on its own local stock market, this paper focuses simultaneously on the impact of China's pandemic on the US stock market and the impact of the US's pandemic on China's stock market, which means this study focuses on the intercorrelation of two countries.

This paper emphasizes the significance of exploring the interaction between countries in the context of a global epidemic and reminds people of considering matters in a broader context.

The results that the pandemic in China inspires the negative consequence of the Nasdaq stock returns remind policy makers, especially the Chinese government of publishing policies to restrict people's irrational behavior driven by the panic brought on by the pandemic. For example, the government can enact laws that restrict citizens from making large and unconscionable transfers of assets to maintain the stability of the stock market. If similar health problems occur in the future and cause panic among citizens, the government should plan ahead to avoid affecting the country and the global economy and to value the physical and mental health of citizens. This paper also implies that investors should consider things and make decisions more rational, even under the pressure from similar situations or when the stock market fluctuates. People also should observe sensibly before making a decision so as not to cause volatility in the global stock market that could affect global economic development.

6. Conclusion

COVID-19 has brought significant to people's lives, and therefore affect people's mood and behavior. Also, the pandemic has led to volatility in the stock market. Although there were already a few pieces of research studying the effect of the stock market, this paper fills the gap where few studies were about how the pandemic of two countries to each other's economy.

This paper uses the daily new confirmed cases in China and the United States to represent the seriousness of the pandemic in both countries. Also, it uses the stock returns of Nasdaq and SSEC to represent the situation of the economy in both countries. Then VAR and ARMA-GARCH models are built, with the VAR model exploring the impulse responses and the ARMA-GARCH model assessing stock returns and conditional variance. This study draws conclusions after conducting an empirical investigation.

Eventually, this article demonstrates that the increase in the new confirmed diagnoses in the U.S. does not have a significant impact on SSE index returns. However, the pandemic in China will affect the U.S. stock market. Since Chinese investor behavior is very susceptible to stress, and sentiment, Chinese investors will move money to other markets in response to the China outbreak, causing volatility in the U.S. market in the long term.

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