The Long-term Impact of Covid-19 on US Stock Market: Evidence from Time Series Model

Jingpeng Zhao
Yuanpei College, Peking University, Beijing, 100091, China
*Corresponding author: 1900017867@pku.edu.cn

Abstract. The COVID-19 had a obvious impact on the world economy. Both the real economy and the financial markets suffered a huge negative impact in the short term. Considerable studies have pointed out that stock markets suffered a considerable negative impact on yields and volatility in the short-term following the outbreak, but few studies have explored the long-term impact of COVID-19 on stock markets. This research hopes to complement this part of the study. This study investigates the impact of the number of daily new cases on the three major U.S. stock indices, i.e., NASDAQ, S&P 500, and DJI yields and volatility, by developing a VAR model and an ARMA-GARCHX model. The results of this study show that the number of COVID-19 new cases will only have a negative impact on stock yields on that day and will not have a long-term impact. And the number of new cases is negatively related to stock volatility. This study shows that after nearly three years of COVID-19 persistence, it no longer causes widespread panic and irrational behavior, and stock volatility has started to fall back. This result helps to build confidence that people will return to the stock market.

Keywords: COVID-19; US stock market; VAR model; ARMA-GARCHX model

1. Introduction

The COVID-19 outbreak may be the most important public event of the 21st century. Compared to previous localized epidemics such as SARS and Ebola, COVID-19 has a much greater contagious capacity, which allows it to spread rapidly across the globe. Since the virus was discovered in Wuhan in January 2020, it took just two months for COVID-19 to spread to over 100 countries worldwide. Based on the severity of the epidemic, WHO declared COVID-19 a worldwide pandemic in March 2020.

The spread of COVID-19 acted as a black swan event, which severely impacted the global economy in the short term. In order to stop the spread of the epidemic, blockade and quarantine policies have been adopted around the world, prohibiting any gathering activities and preventing people from moving from place to place. On the supply side, these policies have hit hard in industries that rely on offline channels, such as transportation, tourism, and restaurants. According to Singh and Neog's study, India's tourism and transportation industries suffered a severe decline during the epidemic, causing a significant impact on the macro economy [1]. Additionally, international trade is difficult to carry out, which heavily affects the development of the global industrial chain. On the demand side, Shapiro's research shows that people have significantly cut back on their consumer demand due to the uncertainty of the outbreak's development [2]. Under the double negative impact of supply and demand side, the real economy of almost all major countries in the world has stepped into depression. In the first half of 2020, all of the world's top 20 economies had negative GDP growth rates. The U.S. unemployment rate soared to 14.8% in April 2020, more than six times the rate in February of the same year.

The depression in the real economy was quickly transmitted to the financial markets. The impact of COVID-19 on the macro economy and the industry is directly reflected in the share prices of the companies. Harjoto et al. showed that the spread of the epidemic had a short-term negative impact on stock markets worldwide, especially on SMEs and emerging market firms, which are less capable to withstand shocks from the black swan events [3]. He et al. explored the impact of the pandemic on the Chinese stock market in various industries. They found that the transportation, mining and electric power industries, which were more affected by the segregation at home policy and could not resume work in time, suffered a greater impact on their stock prices [4]. The impact of COVID-19 on the U.S.

stock market was even more pronounced, as the rapid spread of COVID-19 in the U.S. in March 2020 deepened pessimistic expectations about the future economic situation, and coupled with various negative macro shocks such as the volatility of international crude oil prices, people accelerated their flight from the U.S. capital markets. This directly led to four meltdowns in the U.S. stock market in 10 days in March 2020, compared to a total of only five meltdowns in the history of the U.S. stock market. And Xue and Ren's study points out that among the many negative factors that led to the plunge in U.S. stock prices, the spread of Covid-19 was the biggest contributor. The downward trend in the stock market brought about by the epidemic shock did not ease until the Federal Reserve adopted an extremely accommodative monetary policy in May 2020 [5].

In addition, news of the growing severity of the epidemic deepened people's fears, which led to more irrational behavior in the stock market and pushed up the volatility of the overall stock market in the short term. Li showed that fear of COVID-19 was the main reason for people's frequent attention to the stock market, which in turn led to higher stock price volatility in early 2020. People's decisions to buy or sell stocks are highly dependent on the Global Reported Confirmed Cases Index, the Death Index, and the Fear Index [6]. Baek and Lee examine the short-term impact of epidemic news on U.S. stock market volatility. Their study finds that bad news associated with the epidemic (e.g., increased mortality) increases U.S. stock market volatility, while good news (e.g., increased recover rates) decreases U.S. stock market volatility. But the magnitude of the impact of the bad news and good news on volatility is asymmetric [7]. Onai's study directly points out that the increase in confirmed cases and deaths will cause the VIX to climb rapidly in the short term, which means a significant increase in volatility in the U.S. stock market [8]. In summary, the epidemic has a significant short-term impact on stock returns and volatility.

It is worth noting, however, that the above studies tend to examine only the short-term effects of epidemic news. This may be due to the fact that in the early stages of the epidemic development, most people believed that COVID-19 would not persist for long. Today, however, COVID-19 has persisted for almost 3 years and the epidemic shows no sign of ending anytime soon. This leads this paper to continue exploring the long-term effects of COVID-19 on the stock market. In particular, since the emergence of the Omicron strain, COVID-19 has emerged with a more infectious and less lethal image. Some countries no longer have a complete quarantine prevention policy, which has allowed some industries mainly in the offline channel to recover. And as people become more aware of COVID-19, they are less likely to become overly alarmed by COVID-19. All of these facts mean that the long-term impact of the epidemic on the stock market is likely to be much more moderate than the short-term impact it causes. Therefore, as a complement to the above studies, this study investigates the long-term impact of COVID-19 on the U.S. stock market by constructing an ARMA-GARCHX time series model.

The U.S. stock market was chosen as the subject of this study because it is representative. The U.S. stock market is the largest financial market in the world, and its movements tend to influence the movements of other stock markets, and its volatility also tends to have spillover effects on other stock markets. Mumtaz and Moon's studies respectively points out that there are volatility spillovers effects from U.S. stocks to Chinese stock markets and to stock markets in developed Europe [9][10]. Aladesanmi's study also demonstrates a closer link between US and UK stock market yields and volatility following the formation of EMU [11]. The study by Song et al. even points out that the Ganger causal effect between the U.S. and Chinese stock markets is more pronounced after the epidemic crisis than before the epidemic [12]. Thus, by examining the long-term effects of the epidemic on U.S. stocks, a rough idea of the long-term impact of the epidemic on global stock markets can be get.

The article is as follows: section 2 will present the data and model settings used in the study, Section 3 will give the empirical results obtained using these models, Section 4 will discuss the findings obtained in this paper through the empirical results, and Section 5 is a conclusion.

2. Research Design

2.1 Data and Resources

To investigate the U.S. stock market, the three major indices, NASDAQ, S&P 500 and DJI, are represent the overall U.S. stock market. As for the COVID-19, the number of new diagnoses per day is the indicator of the development of the epidemic. All data used in the research span from January 15, 2020 to August 21, 2022. The data used in the study are all from wind, a Chinese financial database.

2.2 Stationary Tests

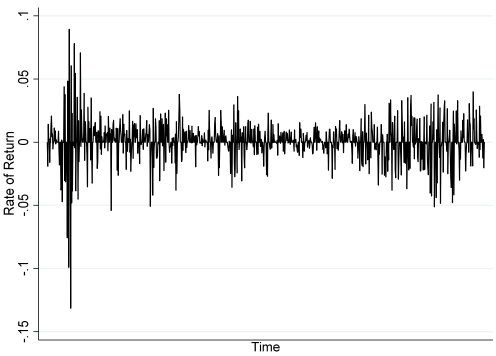
In order to use the ARMA model, the time series used need to be stationary. ADF test can be used to test the stationarity of a single time series. A time series is stationary when the original hypothesis of the ADF test can be refused. The results of the ADF tests for the logarithms of the NASDAQ, S&P 500, and Dow Jones indices, as well as their first-order differences (i.e., yields) and the logarithms of the number of new diagnoses per day, are shown in Table 1.

Table 1 ADF test

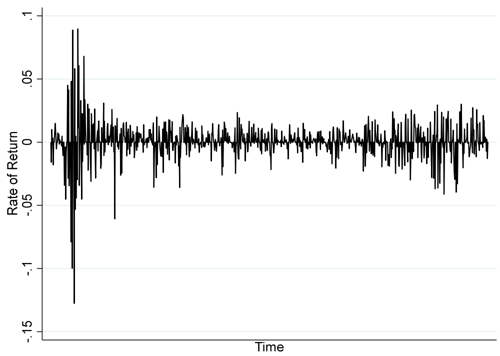
Variables	t-statistic	p-value
Price		
Nasdaq	-1.167	0.9171
S&P 500	-1.677	0.7609
DJI	-2.142	0.5227
Yield		
Nasdaq	-22.845	0.0000***
S&P 500	-22.346	0.0000***
DJI	-21.367	0.0000***
New daily confirmed cases		
Global	-4.264	0.0036***

The results above show that the logarithm of the number of new diagnoses per day is stationary, while the logarithm of the three stock indices is not stationary. The first-order differences of the logarithmic values of the three indices, which means the yield series are stationary. Therefore, when constructing models, yields of the indices are used. Figure 1 shows the time series of yields of these three indices.

Nasdaq



S&P 500



DJI

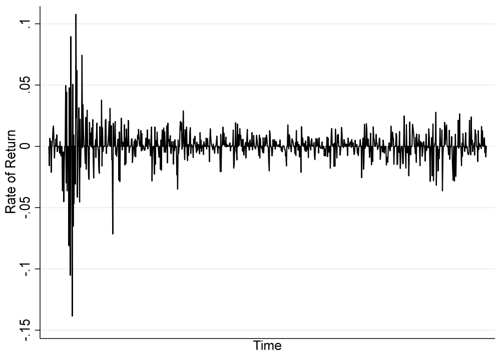


Figure 1 Yield trend

Intuitively, from Figure 1, there is some clustering about the volatility of the yield trends of all three indices. This research will construct ARMA-GARCHX models later to investigate whether the clustering of these volatilities is significant

2.3 VAR model

In order to investigate simultaneously the intercorrelation between the three stock indices and the number of new diagnoses per day, a VAR model about these four variables is constructed. The model was constructed as follows.

$$X_t = \alpha_t + \sum_{i=1}^{p} \Pi_i X_{t-i} + U_t \tag{1}$$

In the formula, X_t represents a 4*1 column vector of time series variables, including the return on the NASDAQ, the return on the S&P 500, the return on the DJI, and the logarithm of the number of new diagnoses per day. α_t represents a 4*1 column vector of constants. Π_i represents a 4*4 matrix of coefficients. U_t is a column vector of random errors, $U_t \sim IID(0, \Omega)$. p represents the order of the lag of the VAR model. The p will be determined later in the empirical section. Using this VAR model, the inner dynamics relationship between these four variables can be investigated. At the same time, the impulse function can be used to study the effect of a change in one variable on the values of other variables several periods later.

2.4 ARMA-GARCHX model

An ARMA-GARCHX model is used to investigate the conditional heteroskedasticity of the three major stock indices and to explore the effect of the number of new diagnoses per day on the volatility of the three indices. The ARMA part of the model is as follows.

$$y_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i y_{t-i} + a_t - \sum_{i=1}^{q} \theta_i a_{t-i} \tag{2}$$

In the formula, y_t represents the time series of yields of the three major stock indices this research investigates, respectively. $\varphi_0 + \sum_{i=1}^{p} \varphi_i x_{t-i}$ is an AR(p) model that uses the values of the past p periods for forecasting. $a_t - \sum_{i=1}^{q} \theta_i a_{t-i}$ is an MA(q) model that uses a perturbation term estimated from past values to make predictions for current period data. The p, q will be determined later in the empirical section.

The GARCHX part of the model is set up as follows.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \gamma_i \sigma_{t-i}^2 + \beta * x_t \quad (3)$$

In the formula, σ_t^2 represents the time series of the variance of the yields of the three indices respectively, which measures the volatility of the three major stock indices. $\alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2$ is the ARCH term in the model, using the perturbation term estimated from the past variance for forecasting. $\sum_{i=1}^{q} \gamma_i \sigma_{t-i}^2$ is the GARCH term in the model, which uses past variance values to make a forecast of the current period variance values. x_t represents the logarithm of the number of new diagnoses per day. Generally for time series analysis, GARCH (1, 1) is sufficient, so in this research, $p = q = 1$. Using the ARMA-GARCHX model, this research can explore the intrinsic aggregation of volatility in the three major stock indices, as well as the direct impact of daily confirmed cases on the volatility of the three indices

3. Empirical results

3.1 VAR model

Before using the VAR model for analysis, its lag order need determining. The commonly used criteria for determining the order are LR, AIC, HQIC and SBIC. The results of using these methods to determine the order are shown in Table 2.

Table 2 VAR model identification

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	8991.42	-	-	-	4.5e-14	-19.3903	-19.3824	-19.3695
1	10756.2	3529.5	16	0.000	1.0e-15	-23.1632	-23.1235	-23.0590
2	10778.7	45.081	16	0.000	1.0e-15	-23.1773	-23.1058	-22.9897
3	10835.0	112.61	16	0.000	9.3e-16	-23.2643	-23.1609	-22.9933
4	10861.8	53.656	16	0.000	9.0e-16	-23.2877	-23.1525	-22.9332
5	10918.5	113.37	16	0.000	8.3e-16	-23.3754	-23.2084	-22.9376
6	11030.8	224.63	16	0.000	6.7e-16	-23.5832	-23.3844	-23.0620
7	11042.1	22.612	16	0.125	6.8e-16	-23.5731	-23.3425	-22.9685
8	11180.5	276.80	16	0.000	5.2e-16	-23.8372	-23.5747	-23.1492
9	11250.0	138.97	16	0.000	4.7e-16	-23.9526	-23.6583*	-23.1812*
10	11258.0	15.971	16	0.455	4,7e-16	-23.9353	-23.6092	-23.0805
11	11284.0	51.964*	16	0.000	4.6e-16	-23.9568*	-23.5989	-23.0186
12	11289.0	10.017	16	0.866	4.7e-16	-23.9331	-23.5434	-22.9115

In Table 2, each row marked with a star represents the optimal order of the VAR determined by specific method. It is shown that the optimal order obtained using LR and AIC statistics is 11, and the optimal order obtained using HQIC and SBIC is 9. In general, a larger number of parameters in the model makes the likelihood of bias and overfitting problems higher. Therefore, the smaller of the two, which is 9, is chosen as the lag order in this study.

After deciding on the lag order, the model built here needs to be stationary, which means that the eigenvalues of the coefficient matrix need to all fall within the unit circle. The distribution of the eigenvalues of the coefficient matrix is shown in Figure 2 below.

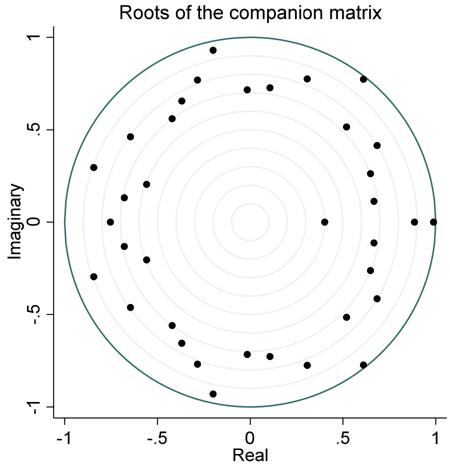


Figure 2 Unit circle test

Each black dot in Figure 2 represents an eigenvalue of the coefficient matrix. From the figure, it can be seen that all eigenvalues fall within the unit circle, which the VAR model built is satisfied with the stationarity.

After establishing the VAR model, the impulse function can be used to investigate the intrinsic correlation between the variables. Here, the impact of changes in the number of new diagnoses per day on the yields of the three major stock indices is focused on. The impulse function graph is shown in Figure 3.

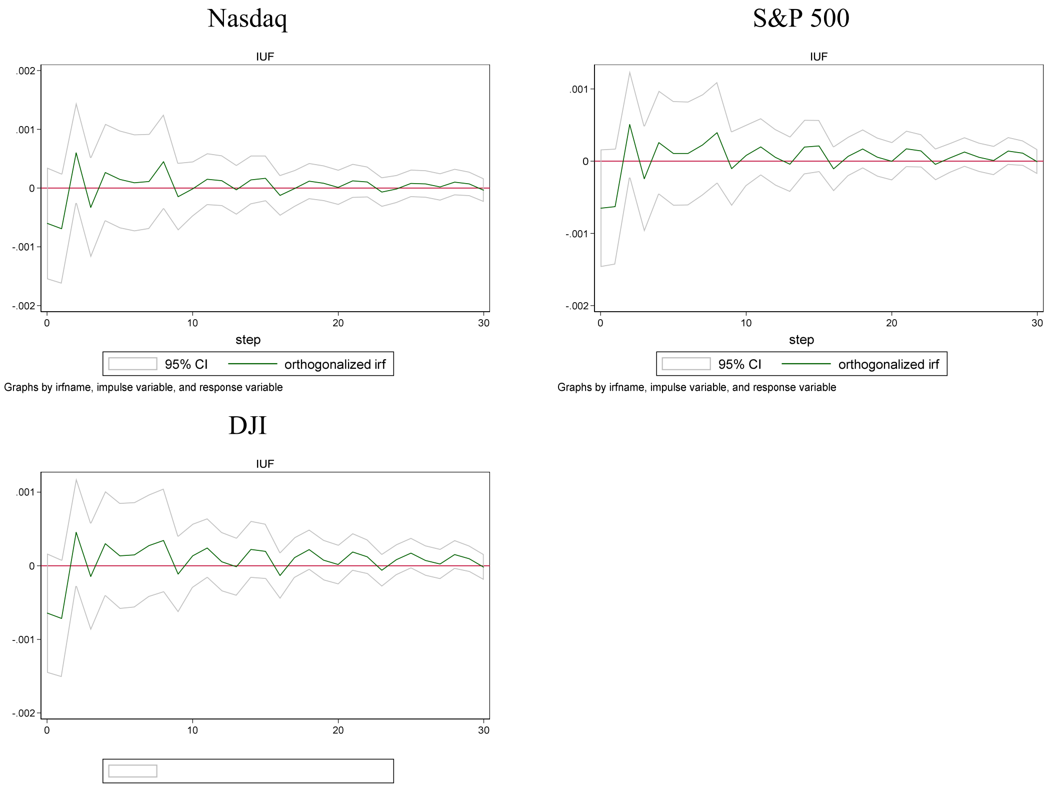


Figure 3 Impulse and response

As can be seen from Figure 3, the impulse functions are very close in shape. When the number of new diagnoses per day increases by about 1%, the yields of the three major stock indices react quickly on the same day, causing a decrease of about 0.1%. This was followed by a quick change to positive the second day. After that, the impulse function tends to smooth and oscillates around 0. This means that thw increase in the number of new diagnoses per day affects stock yields almost exclusively on that day, and has little effect on later stock yields.

3.2 ARMA-GARCHX model

Similarly, before using the ARMA model, determining the lag order of the AR part and the MA part is essential. The PACF and ACF functions are generally used to determine the orders of the AR and MA parts. The PACF function and ACF function of the three major stock index yields are shown in Figure 4.

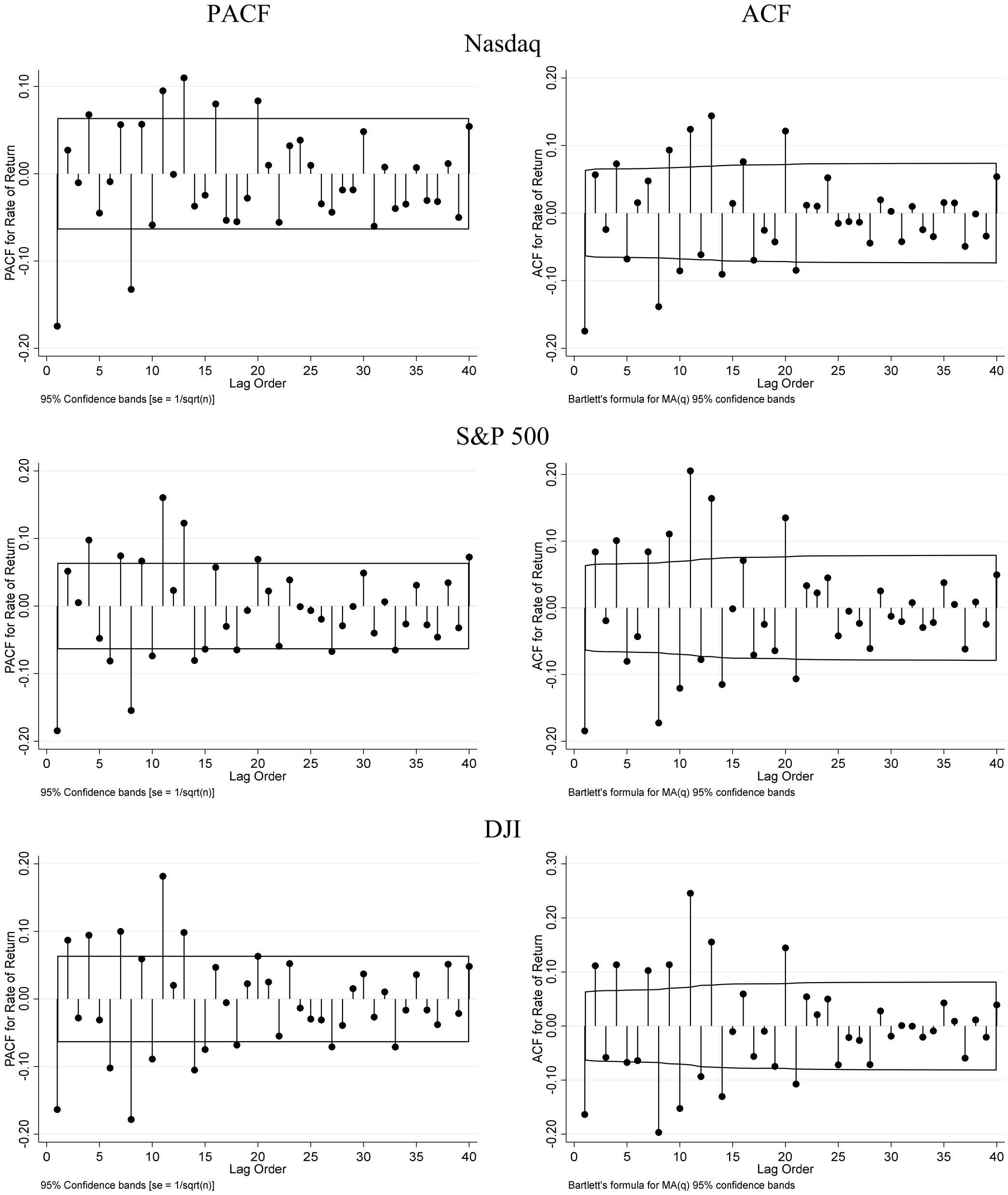


Figure 4 PACF and ACF

In the PACF function, the smallest order above the 95% confidence band is the order of the AR part. As can be seen from Figure 4, the first-order PACFs of all three major stock indices exceed the 95% confidence band, so the lag order of their AR parts are all 1. Similarly, for the ACF function, the smallest order above the 95% confidence band is the order of the AR part. From Figure 4 shows that the lag order of their MA parts is also 1.

After deciding on the lag order of the ARMA component, an ARMA-GARCHX model can be built to investigate the relationship between the volatility of the three major stock indices and the number of new diagnoses per day. Table 3 shows the estimated values of the coefficients of the ARMA-GARCHX model built in this study

Table 3 ARMA-GARCH estimation results

	(1) Nasdaq		(2) S&P 500		(3) DJI	
	Coefficient	p>|Z|	Coefficient	p>|Z|	Coefficient	p>|Z|
Daily confirmed cases	-0.3220	0.0000	-0.2975	0.0000	-0.3276	0.0000
ARCH, L1	0.0936	0.0000	0.1182	0.0000	0.1236	0.0000
GARCH, L1	0.8893	0.0000	0.8585	0.0000	0.8436	0.0000
Constant	-8.3768	0.0000	-8.8195	0.0000	-8.3029	0.0000

As seen in Table 3, the ARCH and GARCH coefficients of the three major stock index yields are all significant. This suggests that there is indeed a volatility clustering in the three stock indices, which satisfies the basic conditions for GARCH model. It is worth noting that the coefficient of the number of new diagnoses per day is significantly negative. This means that at this time, an increase in the number of daily new cases will instead make the stock less volatile.

4. Discussion

This research investigates the long-term impact of the epidemic development on the U.S. stock market by constructing a VAR model and an ARMA-GARCHX model. The impact of the number of new diagnoses per day on the yield and volatility of the three major indices of the U.S. stock market (i.e., Nasdaq, S&P 500, and DJI) after the epidemic becomes normalized is explored in this research.

On the yield side, the increase in the number of confirmed cases per day after the normalization of the epidemic will still have a negative impact on US stock yields, but this negative impact is not sustainable. On the second day, this negative impact ceases to exist. This means that with the epidemic now becoming normalized, the development of the epidemic is no longer going to have a lasting impact on the stock market. The impact of the epidemic on the stock market has now become mild and short-lived, especially compared to the short-term dramatic impact it had on the stock market at the beginning of the epidemic.

In terms of volatility, the results obtained in this study are even more surprising. The results of this study showed that as the number of new diagnoses per day increased, the stock market became significantly less volatile instead. This is the exact opposite of previous studies in which the development of the epidemic aggravated people's panic in the short term, which in turn led to a significant increase in stock market volatility. One possible reason is that the infectiousness of COVID-19 has increased rapidly with the appearance of new strains of COVID-19 such as Omicron, bringing about a rise in daily confirmed cases. At the same time, the death rate of confirmed cases began to decline, allowing people to stop panicking over news of the outbreak. As a result, stock market volatility began to fall back to a relatively normal level. This result indicates that news of the outbreak no longer has a significant impact on stock market volatility.

In summary, this study finds that although the epidemic has brought a strong short-term impact on financial markets, the impact of the epidemic news on equity markets has moderated in the long run. It is foreseeable that the impact of the outbreak on financial markets will continue to diminish in the absence of a significant increase in COVID-19 mortality rates. Therefore, for the average investor, there is reason to believe that the additional risk posed by the epidemic will be gradually eliminated. One can continue to enter the stock market using normal investment logic. As for policymakers, the results of this research suggest that the normalization of the epidemic will not have a significant long-term impact on financial markets. This implies that policymakers can adopt a more even-handed approach to COVID-19.

5. Conclusion

This research investigates the long-term impact of COVID-19 on the U.S. stock market by developing a VAR model and an ARMA-GARCHX model. The results show that the long-term impact of the epidemic is relatively moderate compared to the short-term impact of the epidemic on financial markets. Additional confirmed cases will still result in some decline in equity returns, but the decline will be relatively low and will not have a lasting impact. And the development of the epidemic has largely refrained from causing panic and irrational behavior, and the volatility of the stock market has started to fall back. These results suggest that during the more than two years that COVID-19 has persisted, the U.S. stock market has largely stopped reacting to news of the epidemic as its mortality rate has declined and awareness of it has gradually increased. People are increasingly rationalizing their investment behavior in the U.S. stock market. Maybe now, it's already a good time to get back into the stock market.

References

[1] Singh M K, Neog Y . Contagion effect of COVID outbreak: Another recipe for disaster on Indian economy. Journal of Public Affairs, 2020.

[2] Shapiro A H. Monitoring the Inflationary Effects of COVID-19. FRBSF Economic Letter, 2020.

[3] Harjoto M A, Rossi F, Paglia J. COVID-19: Stock Market Reactions to the Shock and the Stimulus. Applied Economics Letters, 2020, Forthcoming 2020.

[4] [He, Sun, Zhang, et al. COVID–19's Impact on Stock Prices Across Different Sectors—An Event Study Based on the Chinese Stock Market. Emerging Markets Finance & Trade, 2020.

[5] Gao X, Ren Y, Umar M. To what extent does COVID-19 drive stock market volatility? A comparison between the U.S. and China. Ekonomska Istraživanja / Economic Research, 2021:1-21.

[6] Li W, Chien F, Kamran H W, et al. The nexus between COVID-19 fear and stock market volatility. Ekonomska Istraivanja / Economic Research.

[7] Baek S, Lee K Y. The risk transmission of COVID-19 in the US stock market. Applied Economics, 2021, 53(17):1-15.

[8] Enrico Onali. COVID-19 and Stock Market Volatility 2021. 2021[2022-09-13]. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3571453

[9] Mumtaz M Z, Smith Z. Examining Spillover Effect of Us Monetary Policy to European Stock Markets: A Markov-Switching Approach. Social Science Electronic Publishing.

[10] Moon G H , Yu W . Volatility Spillovers between the US and the China Stock Markets: Structural Break Test with Symmetric and Asymmetric GARCH Approaches. Social Science Electronic Publishing.

[11] Aladesanmi O. Modelling spillover effects between the UK and the US stock markets over the period 1935–2020. Investment Analysts Journal.

[12] Song, Ge, Zhiqing Xia, Muhammad Farhan Basheer, and Syed Mehmood Ali Shah. Co-Movement Dynamics of US and Chinese Stock Market: Evidence from COVID-19 Crisis." Economic Research-Ekonomska Istrazivanja, 2021, July, 1–17.