The Impact of COVID-19 Pandemic on the Social Media Industry: A Long-term Perspective

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Abstract. With the emergence of the coronavirus pandemic around the world, social media has rapidly become an effective tool for information generation and broadcast, entertainment, marketing, and consumption. Depending on some studies, social distancing rules, lockdown measures, business closures, self-quarantines, and the fear of infection during the COVID-19 pandemic limited people's physical social interaction; as a result, individual and organizational activities on social media platforms grow explosively. This degree of social media popularity has a double-edged impact on the expansion and financial performance of social media companies. In this article, a well-known American corporation, Twitter, Inc. was chosen and daily stock data from January 2020 to April 2022 is extracted, as well as corresponding daily new confirmed cases in the US and around the world. The VAR model was applied in the study to evaluate the link between variables, and the ARMA-GARCH model was used to determine and analyze both earning ability and stock volatility throughout the pandemic. Interestingly, Twitter's financial performance is merely a microcosm of the entire stock market, in which investors can quickly rebound from pessimism and reinvest in the market. The study forecasts the possible future of the social media industry and provides managerial and investment recommendations to its stakeholders.

Keywords: COVID-19 pandemic; Social media industry; Stock returns; Stock return volatility; Twitter.

1. Introduction

The National Science Foundation Network (NSFNET), the basis of modern internet and social media, debuted in 1987. This marked the beginning of the social media network's growth [1]. Since the internet's development has expedited the introduction of digital communication and social media networks, there have been some significant milestones in the internet's rapid expansion and rise. Social media global penetration has reached 60% in 2022, with global social media audiences totaling 4.59 billion users, and it is expected to rise steadily over the next five years [2]. Based on decades of research, social media sites and apps have become some of the most essential instruments in this digital era, and they may be regarded a part of people's lives. People use platforms like as YouTube, Facebook, Instagram, Twitter, and Sina Weibo to receive information, stay in touch with friends, fill spare time, and even do business.

Because of the rapid spread of COVID-19, the globe has been in a state of panic and turmoil since the initial report in December 2019 became public and then brought unprecedented issues globally. The social media industry is not an exception; the advent of the pandemic interferes with it. According to the WHO's report on *Social Media & COVID-19: A Global Study of Digital Crisis Interaction among Gen Z* and *Millennials,* approximately 44% of respondents would prefer to post *scientific* content about COVID-19 on social media during the pandemic, rather than entertaining or emotional content [3]. More specifically, between April 9 and April 15, 2020, around 530000 tweets about CORONAVIRUS and COVID-19 were retrieved from Twitter [4]. During the early stages of the pandemic in China, the average number of daily posts about the pandemic on Sina Weibo was around 343000 [5]. These figures indicate that COVID-19 pandemic discourses have spread fast via social media to compensate for restrictions on physical interactions and social contact among people.

Previous research has found close association between social media and the COVID-19, which is involved in politics, health care, education, and marketing. According to Nulty et al., every political party uses social media platforms for politics, and these channels allow those with less budgets to convey their messages inexpensively [6]. Since a list of COVID-19 pandemic hashtags appeared as hot topics on Twitter, 64.8% of UN member states had a leader who tweeted about COVID-19, and there was a considerable growth rate of Twitter followers for leading politicians who used their accounts frequently in comparison to pre-pandemic months [7]. President Donald Trump of the United States, Prime Minister Boris Johnson of the United Kingdom, WHO Director, and numerous European Union presidents are examples of people who use social media to update information and policies on vital problems [8]. In order to promote people's compliance with COVID-19 legislation, governments use such a new and stylish strategy to maximize the possibility of the public reading and learning the latest politics and information from key government sources [7].

Additionally, social networking networks are drawing more medical or health care organizations. Gaini et al., for example, claimed that the majority of US neurology residency programs started Twitter and Instagram profiles after March 1st, 2020 [9]. Research groups and large national and international studies, such as RECOVERY and the EuroELSO survey, were also aggressively recruiting and reporting on Twitter, Facebook, and similar social media platforms [10]. The inclusion of health care studies and programs causes social media to cover not just entertainment but also academic discoveries, thereby expanding key audience demographics. Although social media has a positive impact on raising domestic awareness about preventive measures [11], the amplification, inaccuracies, and misinformation about health [10, 12], as well as the public's relatively negative perspectives on aspects of social media [13], indeed contribute to trustworthiness concerns [8]. In other words, social media usage and activity vary according to the material presented.

Moreover, social media products play important roles in education; for example, some schools decided to adapt e-learning via YouTube [14], to gain digital social support and use collaboration functions in Instagram [15], and to allow radiology students to share videos and make the study more interactive via Facebook Live [16]. These all show that powerful and multifunctional tools spark public participation on social media sites.

Furthermore, many companies attempt to use social media marketing and advertising to raise brand awareness, attract potential consumers, meet customer demands, and achieve targeted conversion rates. According to Statista, companies seeking additional consumers had to pay much more to have their adverts seen by a thousand potential customers from 2020 to 2021 due to an increase in advertising space demand [17]. For example, Nike, a well-known sportswear retailer, offers online exercises through its own channels and social media platforms, providing athletes all over the world with tools, motivation, and affirmation to help fuel physical and mental health [18]. Under the strain of the restaurant shutdown and self-quarantine policy, some takeaway companies, including Hungry Panda and Deliveroo, sought to advertise on Instagram, Twitter, and YouTube. Other companies' exposure on social media may also motivate people to visit these channels more regularly. In terms of more attention and demands for advertising spaces during the pandemic, social media firms appear to be lucrative.

These previous studies highlighted how COVID-19 altered people's and organizations' social media platform usage behaviors and habits. The increased utilization might be attributed to more new contracts, the availability of new products, and a rise in stock price. In that way, it may stimulate stock return volatility. However, only a few studies discussed how exactly the stock volatility of the social media company reacts to changes in the COVID-19 pandemic. To fill the void, this paper examines not only how the increase in confirmed cases in the US affects a specific social media company Twitter in terms of stock volatility, but also how COVID-19 confirmed cases around the world influence a specific social media company Twitter in regard to stock volatility, given that more than 80% of active Twitter users are outside of the US. The specific reason for analyzing the relationship is to understand the fluctuation pattern of a social media firm's stock return after the spread of the COVID-19 pandemic, to determine the differences and similarities with the broad US stock market, and to provide relevant advice to investors and organizations. As a result, some irrational investments or strategies can be avoided.

The remainder of this paper is organized as follows: Section 2 covers information about the data source, data stability, and the models used in this paper. Section 3 follows, with a full discussion of the results from the VAR model and the ARMA-GARCH model, as well as additional analysis on the stock return, stock volatility, and market participants' behavior. Following that, there is a discussion on the study's focus, objective, and importance. Finally, Section 5 reiterates the final conclusion briefly.

2. Research Design

2.1 Data Source

Twitter is one of the most prominent social media platforms with large masses of available data; it can be representative and serve as an example for comprehending the social media industry's pandemic influence. The study extracted daily closing stock prices of Twitter and daily total confirmed cases in the US and around the world from January 23, 2020 to April 13, 2022, from the Choice financial terminal. The rationale for halting data collection till now is to avoid the impact of the issue that Elon Musk made an offer to buy all of Twitter's shares [19]. Data processing is required to figure out the impact of increased new cases in the United States and throughout the world on Twitter stock return fluctuations. To elaborate, today's total confirmed cases in the US and around the world are subtracted from the previous day's total confirmed cases to obtain the daily growth in US and global new cases, and Twitter stock returns are obtained by dividing the difference between two days' closing stock prices by the one on the previous day, and data is transformed by the formula $ln(1+x)$, continuing analysis in the logarithmic scale. Because there are some total confirmed cases lost on specific days, the missing data are omitted during the study. With the updated edited data, Stata was used to analyse the data and construct models for further exploration.

2.2 Augmented Dickey–Fuller (ADF) Unit Root Test

Testing whether or not the data are stationary is the first step before proceeding. Based on the ADF testing conducted in Stata, the p-values in Table 1 for Twitter stock return and daily new confirmed cases in the US and the globe all equal 0, which is considered statistically significant. Due to these findings, there is enough evidence to reject the null hypothesis that the variable contains a unit root. In other words, the model built on the data is feasible and the data are stationary.

Table 1. ADF test

Variables	t-statistic	p-value
Twitter	-15.1340	0.0000***
New confirmed cases		
US	-10.2810	0.0000***
Global	-11.2650	0.0000***

2.3 Vector Autoregression (VAR) Model

The use of the VAR model predates the rise of the VAR approach [20], and it can be traced back to a study On the Statistical Treatment of Linear Stochastic Difference Equations [21] and A Study of the Autoregressive Nature of the Time Series Used for Tinbergen’s Model of the Economic System of the United States [22] before reaching Sim's well-known contribution to VAR model application [23-25]. The VAR model can be employed to capture the relationship between multiple variables while avoiding the challenge of model construction based on rigorous economic theory [26]. Although a few analyses suggested that the COVID-19 announcement had an impact on the social media company, little research suggests that there is a strong intercorrelation between stock returns and rises in daily confirmed cases. In this context, the VAR model was chosen, and there are three separate time series variables, denoted by $x_{t,1}$, $x_{t,2}$, $x_{t,3}$, resulting in a trivariate VAR(p) model.

$$x_{t,1} = \alpha_1 + \emptyset_{11}x_{t-1,1} + \cdots + \emptyset_{1p}x_{t-p,1} + \beta_{11}x_{t-1,2} + \cdots + \beta_{1p}x_{t-p,2} + \delta_{11}x_{t-1,3} + \dots + \delta_{1p}x_{t-p,3} + e_{1t}. \tag{1}$$

$$x_{t,2} = \alpha_2 + \emptyset_{21}x_{t-1,1} + \cdots + \emptyset_{2p}x_{t-p,1} + \beta_{21}x_{t-1,2} + \cdots + \beta_{2p}x_{t-p,2} + \delta_{21}x_{t-1,3} + \dots + \delta_{2p}x_{t-p,3} + e_{2t}. \tag{2}$$

$$x_{t,3} = \alpha_3 + \emptyset_{31}x_{t-1,1} + \cdots + \emptyset_{3p}x_{t-p,1} + \beta_{31}x_{t-1,2} + \cdots + \beta_{3p}x_{t-p,2} + \delta_{31}x_{t-1,3} + \dots + \delta_{3p}x_{t-p,3} + e_{3t}. \tag{3}$$

$$\begin{bmatrix} x_{t,1} \\ x_{t,2} \\ x_{t,3} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \begin{bmatrix} \emptyset_{11} & \cdots & \emptyset_{1p} \\ \emptyset_{21} & \cdots & \emptyset_{2p} \\ \emptyset_{31} & \cdots & \emptyset_{3p} \end{bmatrix} \begin{bmatrix} x_{t-1,1} \\ \vdots \\ x_{t-p,1} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \cdots & \beta_{1p} \\ \beta_{21} & \cdots & \beta_{2p} \\ \beta_{31} & \cdots & \beta_{3p} \end{bmatrix} \begin{bmatrix} x_{t-1,2} \\ \vdots \\ x_{t-p,2} \end{bmatrix} + \begin{bmatrix} \delta_{11} & \cdots & \delta_{1p} \\ \delta_{21} & \cdots & \delta_{2p} \\ \delta_{31} & \cdots & \delta_{3p} \end{bmatrix} \begin{bmatrix} x_{t-1,3} \\ \vdots \\ x_{t-p,3} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix}. \tag{4}$$

The equation (1), (2), (3) above are for Twitter stock return, daily new cases in the US, and daily new cases worldwide, respectively, while equation (4) is in matrix form. To clarify, in equation (1), $\alpha_1 + \emptyset_{11}x_{t-1,1} + \cdots + \emptyset_{1p}x_{t-p,1}$ represents a linear function of past lags of Twitter stock return, while $\beta_{11}x_{t-1,2} + \cdots + \beta_{1p}x_{t-p,2}$ and $\delta_{11}x_{t-1,3} + \cdots + \delta_{1p}x_{t-p,3}$ represent past lags of daily new cases in the US and daily new cases in the world, e_{1t} is the error term. As a result, the variable Twitter stock return is modelled using historical values for the variable and the other two variables. Similarly, the structures of the equations for the remaining two variables are the same, but the variable on the left of the equation and coefficients are changed.

2.4 ARMA-GARCH Model

The ARMA-GARCH model can evaluate both the return and volatility of the Twitter stock. This model is broken down into two sections in this paper: ARMA and GARCH.

2.4.1 ARMA

$$y_t = \emptyset_0 + \sum_{i=1}^{p} \emptyset_i \, y_{t-i} + \alpha_i - \sum_{i=1}^{q} \emptyset_i \, \alpha_{t-i}. \tag{5}$$

The general expression of the ARMA model is displayed in equation (5). The AR(p) is represented by the component $\emptyset_0 + \sum_{i=1}^{p} \emptyset_i \, y_{t-i}$, whereas the rest of the equation is MA(q). AR(p) estimates future value applying past Twitter stock returns from January 2020 to April 2022, whilst MA(q) forecasts using an error term.

2.4.2 GARCH

Then comes another section GARCH. GARCH is derived from ARCH fundamentally, and both treat volatility as a variance to be modelled [27]. In this paper, GARCH (1,1) was taken into account, where the first 1 denotes one autoregressive lag and the second 1 denotes one moving average lag. The reasons for selecting GARCH (1,1) are as follows: it has fewer parameters than ARCH(p); it fits many time series well [28], it is sufficient to capture the volatility clustering in the data mentioned in Introductory Econometrics for Finance ed Third [29], and it only requires one lag for analysis [29]. As a result, the model GARCH (1,1) was picked.

$$\sigma_t^2 = \alpha_{0,1} + \alpha_1 \varepsilon_{t-1}^2 + \beta_t m_t + \gamma_1 \sigma_{t-1}^2. \tag{6}$$

In the equation (6), term $\alpha_1 \varepsilon_{t-1}^2$ is ARCH part and $\gamma_1 \sigma_{t-1}^2$ represents GARCH part, and the additional term $\beta_t m_t$ other than the generalised formula represents confirmed cases that acted as an extra explanatory variable in the model.

3. Empirical Results and Analysis

3.1 Order of VAR Model

To find out the optimal lag order for a VAR model, the LR statistic and other information criterion of each lag should be assessed. An asterisk sign (*) appears after the data to signify the desired lag order.

Table 2. VAR model identification

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1199.5600				0.07185	5.8804	5.8921	5.9099
1	-1152.3000	94.5160	9	0.0000	0.0595	5.6934	5.7399	5.8111
2	-1138.0000	28.6020	9	0.0010	0.0580	5.6674	5.7490	5.8735
3	-1119.3200	37.3640	9	0.0000	0.0553	5.6201	5.7366	5.91454
4	-1097.6900	43.2480	9	0.0000	0.0520	5.5584	5.7098	5.9411
5	-843.7530	507.8800	9	0.0000	0.0157	4.3606	4.5470	4.8317*
6	-826.3720	34.7630	9	0.0000	0.0150	4.3196	4.5409*	4.8790
7	-812.7910	27.1620	9	0.0010	0.0147	4.2972	4.5535	4.9449
8	-803.5110	18.5600	9	0.0290	0.0147	4.2959	4.5871	5.0319
9	-785.9930	35.0360*	9	0.0000	0.0141*	4.2542*	4.5804	5.0785
10	-778.4890	15.0080	9	0.0910	0.0142	4.2615	4.6226	5.1742
11	-777.7230	1.5312	9	0.9970	0.0148	4.3018	4.6978	5.3028
12	-773.1160	9.2147	9	0.4180	0.0151	4.3233	4.7543	5.4126

Table 2 reveals that lags 9, 6, and 5 all have that sign. A comparison of AIC differences is necessary to determine the optimal lag order. The difference in AICs between lags 9 and 10 is around 0.1, while the difference between lags 5 and 6 is approximately 0.4. As a result, lag 9 is the better option to start with. Furthermore, despite the fact that both FPE and AIC with an asterisk sign are smallest for lag 9, HQIC and SBIC suggesting other alternative orders, the present optimal lag order for VAR model should be 9.

Following the specification of the VAR model's order, it is crucial to examine whether or not the VAR model is stationary. If the VAR model is non-stationary, the impulse-response function will not converge to zero, indicating that daily new cases have long lasting effects on the Twitter stock return. After that, the model's applicability was determined by carrying out the unit root test and sketching a unit circle with the roots. All of the roots are clearly within the circle in Fig. 1, implying that there is no need to revaluate the lag order and that trivariate VAR(9) is a stable model.

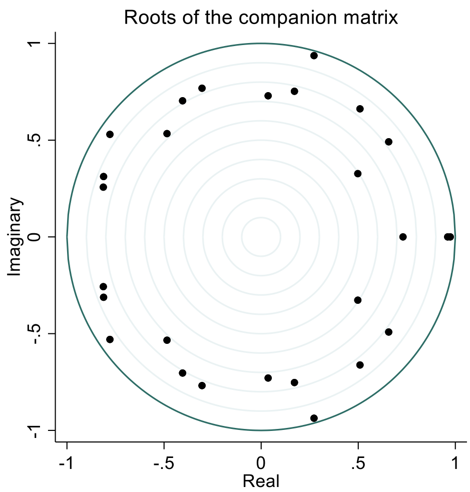

Fig. 1 Unit root test

3.2 Impulse Response

The impulse response function quantifies the time profile of a shock's effect on the behaviour of a series [30]. In this paper, investigation on how Twitter stock returns respond to new case impulses in the United States and around the world was done. Previous research found that a high level of policy uncertainty had a detrimental impact on stock market performance because investors or market participants were pessimistic about the expected discount rate, resulting in a reduction in stock price [31]. Likewise, people were more concerned about the future performance of the stock market, wherever they were, after a short period of the spread of COVID-19 policy, such as physical restrictions and travel bans, and a surge in death. These investors were terrified of the substantial chance of benefit loss. As a consequence, massive capital flowed out of the financial market, causing in a cliff drop in the financial index at the beginning of the outbreak. For example, stocks in the United States, Europe, and Asia fell by approximately 40%, 40%, 20% to 25%, respectively, in March 2020 compared to January 5, 2020 [32]. The stock has been cut by nearly half on March 20 2020, as reflected in the US stock market index US30 (Fig. 2), provoking the panic until March 25. In such a short period of time, the stock recovered brilliantly, soaring over 20% above the previous low. Notwithstanding the deeper understanding of the COVID-19 pandemic, whether or not the changing pattern will continue to be like a roller coaster ride, investors' behaviour will return to normalcy, or the impact will be long-lasting, requires more evidence in long-term perspective.

Fig. 2 US stock market (US30) fluctuation

Note: United States Stock Market Index (US30) changes from January 24 2020 to August 31 2020, extracted from TRADING ECONOMICS, https://tradingeconomics.com/united-states/stock-market

As shown in the impulse response diagram (Fig. 3), when the US daily new cases climb by 1% at t = 0, between t = 0 and t = 4, the Twitter stock return has a clear negative impact. However, it suddenly exerts the greatest positive influence on stock returns at t = 7, with a figure of around 0.3%, and the effects continue to be positive in general beyond t = 7. The global daily new cases have the same effect on the stock return. Both shocks in daily new cases have an adverse impact at first but revert to zero after 20 steps, rather than staying in a long-period pessimistic situation.

Having said that, it appears that investors failed to learn from previous experiences, as the severe impact to the social media business had not deterred their investment. This supports Hsu and Tang's conclusion that the size of the effect of investor sentiment on unanticipated volatility declined later in the pandemic [33]. Twitter’s stock performance is almost a microcosm of the world's stock market.

It is history repeating as the entire stock market performed in 2020, but shorter time intervals have been used for the recurrence.

One thing to note is that, in the context of pandemic normalisation, investors' concern has faded gradually, and there are fewer repercussions on the extent of Twitter stock return.

US Global

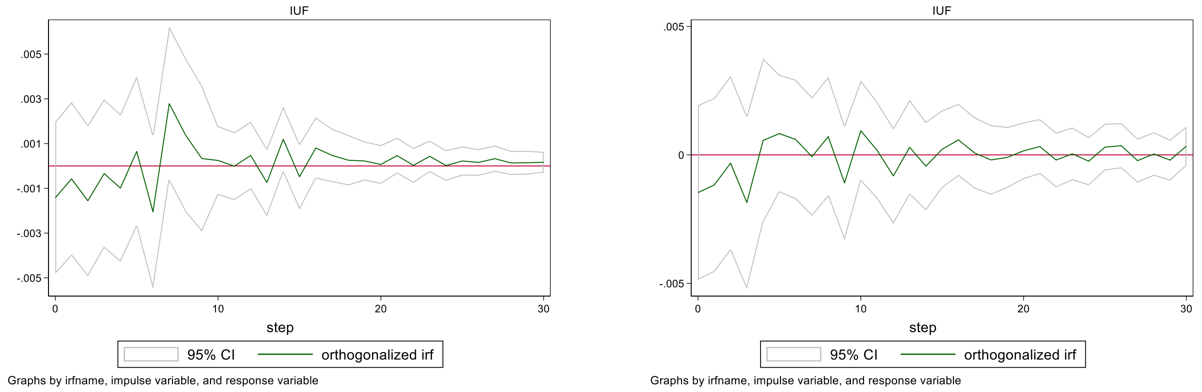

Fig. 3 Impulse and response

3.3 ARMA Specification

Regarding to the order of the stock return in logarithm, PACF and ACF can be helpful to derive the lag orders for AR(p) and MA(q). In the Fig. 4, the first part beyond the critical values is 2 for both PACF and ACF plots, demonstrating that AR(p) and MA(q) both have order 2 and value of p and q are equal to 2.

PACF ACF

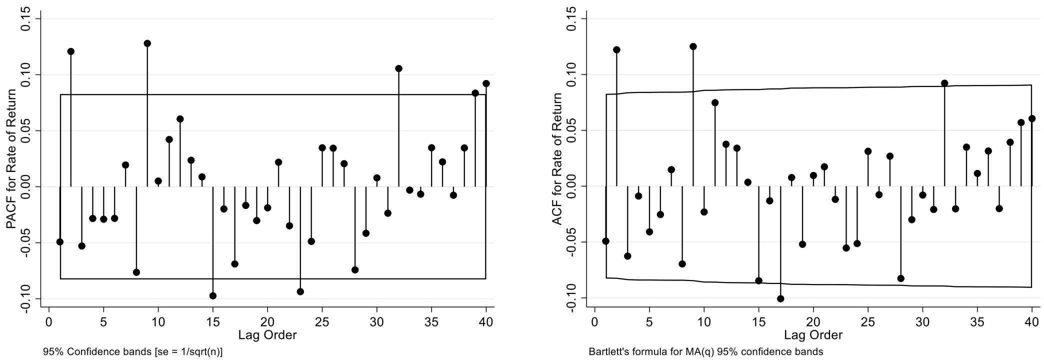

Fig. 4 PACF and ACF

3.4 ARMA-GARCH Estimation Eesults and Variance Equation

As described in Section 2.4.2, implementing GARCH(1,1) is adequate to capture volatility clustering in time series, hence the ARMA-GARCH model was built.

Fig. 5 depicts the characteristics of Twitter stock return volatility. This time series data clearly exhibits overt volatility clustering at the beginning, middle, and end of the periods, revealing conditional heteroskedasticity. However, drawing conclusions solely from the plot is invalid; it would be more logical and reasonable to examine other information about the statistical significance of conditional heteroskedasticity in the model estimation results.

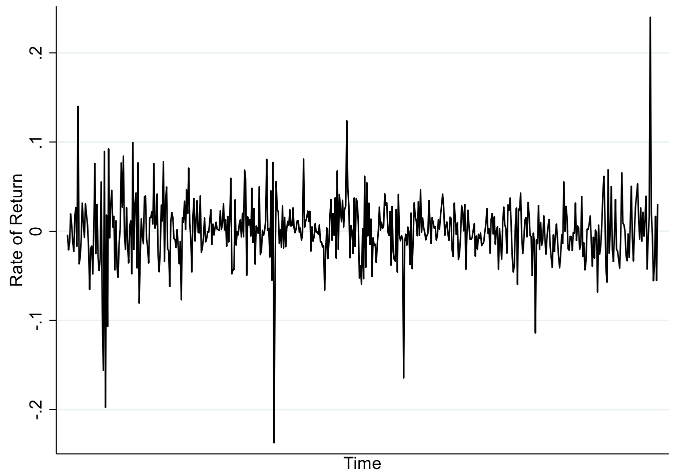

Fig. 5 Yield trend

Table 3 contains the model estimation findings as well as the variance equation. The ARCH and GARCH terms in the variance equation both have p-values less than 0.05, showing that they are significant. The presence of conditional heteroskedasticity fulfils the principal requirement of GARCH model building, implying that the Twitter stock return has significant conditional heteroskedasticity. Both coefficients for the AR model and the MA model have p-values greater than 0.05, meaning that they are insignificant and that there is insufficient evidence to reject the null hypothesis that the coefficients should be 0. The growth of daily new instances in the United States or around the world, in particular, will have no substantial impact on the volatility of Twitter stock returns.

Table 3. ARMA-GARCH estimation results

	(1)			(2)		
	Coefficient	Std. err	p>|Z|	Coefficient	Std. err	p>|Z|
			Mean equation			
AR, L2	0.0010	0.3891	0.9980	0.0052	0.3930	0.9890
MA, L2	0.1293	0.3867	0.7380	0.1257	0.3900	0.7470
Constant	0.0013	0.0017	0.4330	0.0013	0.0017	0.4570
			Variance equation			
New confirmed cases						
US	-0.0304	0.0159	0.0560			
Global				-0.0031	0.0149	0.8350
GARCH (1, 1)						
ARCH, L1	0.2393	0.0433	0.0000	0.2361	0.0441	0.0000
GARCH, L1	0.3870	0.1549	0.0130	0.3439	0.1613	0.0330
Constant	-7.3199	0.3367	0.0000	-7.4666	0.3199	0.0000

4. Discussion

In comparison to other studies, this paper focuses on how COVID-19 US and global new cases affect the stock return and stock return volatility of an American social media company, whereas existing articles discuss the impact of the COVID-19 pandemic on mental health, living habits, interactive behaviors, information dissemination or infodemic [34] on social media. Although some articles investigate stock market performance during the pandemic, their conclusions and topics are more related to big industries such as communication services, technology, healthcare, energy, and so on. However, one similarity between us in analyzing stock market volatility is that many authors adopted methodology or related transformations such as VAR model, GARCH model, TGARCH model [35], EGARCH model [33], or others in their research to determine stock market movements.

Through this paper, managers of social media companies could pay more attention to designing contingency strategies for the emergence of potential black swan events in order to avoid the creation of a bad atmosphere, as well as taking a broad view to judge the likely duration or possible normalization of events, so that public sentiment on social media is under control and can generate much more value than just misinformation exaggeration. Further, supervise stakeholders and market participants with social media accounts, such as policymakers or organizations, taking responsibility to regulate and assure the direction of the discussion is vital, especially in the case of an accident.

In the digital age, social media, as a multitasking tool, typically moves swiftly. The COVID-19 pandemic is only a temporary setback for this industry, and it serves as a reminder for social media companies to improve the current functions and characteristics of their products. According to the findings of this study, it is important for investors who are concerned about social media stocks to forecast the industry's stability and the durability of event impacts on the social media business. Therefore, investors need keep an eye on the latest news in order to modify their short-term investment strategies.

5. Conclusion

The objective of this study is to look into how new cases of the COVID-19 pandemic correlate to the social media industry in terms of usage, stock return, and stock volatility, with an emphasis on the American social media company Twitter. VAR and ARMA-GARCH models are introduced for this purpose, with the VAR model exploring impulse response and the ARMA-GARCH model assessing stock returns and conditional variances. The study leads to a conclusion after conducting empirical investigation.

Finally, this article demonstrates that the public's unexpected boost in use of social media sites during the pandemic does not indicate a continual development or fall of an industry, but rather a short-term shock. Despite the fact that social media penetration and user engagement are increasing every single year, the detrimental impact of the COVID-19 pandemic was only apparent at the beginning. The impact on the long-term future of the social media stock return and its volatility will eventually diminish and return to normal, following the general trend of the stock market.

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