# The Long-term Impact of Covid-19 on Game Industry: Evidence from Daily New Confirmed Cases

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**Abstract.** In early 2020, the Covid-19 outbreak caused turmoil in global financial markets, and among the many industries that suffered severely, the gaming industry stood alone, instead growing explosively in the early stages of the outbreak. However, there was a plunge after 2021. This study evaluates how the pandemic has affected gaming markets in China and other international locations. In order to examine changes in the gaming sector in terms of ROE and volatility, a VAR model and an ARMA-GARCH model are built. This study discovers that unexpected epidemic outbreaks have a mainly beneficial influence on the ROE of the gaming sector, but that this advantage gradually diminishes over time as the normal epidemic eventually lessens investor worry. In the environment of a regular epidemic, investor panic is no longer as severe and the impact on gaming industry yields is quantitatively insignificant. Therefore, investors should invest rationally in this sector.

**Keywords:** COVID-19, Rate of return on investment, Game industry.

## 1. Introduction

The outbreak of COVID-19 in early 2020 threw the entire world into chaos for a long time to follow. The unprecedented infectious capacity of the coronavirus allowed it to quickly spread its tentacles to all corners of the world. Around 600 million confirmed cases and more than 6.5 million fatalities have been reported to date globally [1]. The way of life of citizens around the world has changed dramatically under the threat of infection and even death: working and communicating online has become a normal part of life, and the reduction or even suspension of production of a large portion of goods is unavoidable. For most companies, they reduce the risk of facing the epidemic by reducing the frequency of their economic activities and wait for the return of opportunities in the downturn. According to Luka Vidovic's findings, the airline; automotive; energy equipment and services; hotel, restaurant and leisure; and specialty retail sectors have received an unprecedented impact. Airlines saw the greatest increase in default risk during the period, going from a median default risk of 1.75 percent at the beginning of 2020 to 4.79 percent in January 2022—a shift of 174% [2]. Despite the devastation COVID-19 has caused to sectors that rely on in-person interaction, the need for technology for distant employment and business transactions has dramatically increased due to geographical constraints. Businesses of all stripes are increasing their IT spending. Information technology and government scored well in comparison to other industries. In response to the pandemic, Amazon added 400,000 jobs in 2021 and nearly doubled its workforce, while non-store retailers' revenues rose by 15% from February to April 2020 [3]. Studies show that COVID-19 was even more damaging to the macroeconomy than the SARS epidemic of 2003. It inevitably leads to a dramatic short-term contraction in global consumption, investment, service sector and industrial production activity, and the impact feeds through in stock markets around the world in tandem. The literature demonstrates a substantial correlation between stock market returns and pandemic outbreaks, providing a solid foundation for research into how much an industry is affected by an epidemic. According to behavioral economics, stock markets react more quickly to increases in the number of confirmed cases than to rises in the number of fatalities, and even if infection rates keep rising, stock markets might start to recover when the disease spreads more slowly than anticipated. This suggests that stock market reactions are also inextricably linked to the stage of epidemic development. The potential resilience and complexity of the market makes the study of the impact received by specific industries in an epidemic always relevant.

One of the few industries to make it through the early stages of the epidemic was the game industry, which is the sector responsible for the creation, promotion, and monetization of video games. This is because, compared to many other economic sectors that are badly impacted by pandemics, the video game business is typically more resilient to influenza pandemics. The majority of video game creators, publishers, and operators were able to continue their businesses with personnel who could work from home to support game creation and digital distribution. The history of gaming is much richer than just the 2020 and 2021, but the pandemic has ignited a period of exceptional growth for the sector. Search data from the first few months of the 2020 embargo highlights the explosion in the number of people getting into gaming. Twitch, the most popular live gaming platform in the world, had an 83 percent year-over-year surge in viewing when the pandemic struck, with 5 billion hours of its programming watched in the second quarter of 2020 alone, according to studies by Streamlabs and Stream Hatchet. Those without access to consoles or PCs may now immerse themselves in the gaming world and feel a part of the community by watching live streaming. In addition to that, the number of people aged over 60 searching for games has increased 200% along with the 93% of growth of under-18s who became regular players. On the other hand, global spending on paid downloads and in-game content has grown by 12 and 21%, respectively, in the digital gaming industry [4]. In terms of overall game time, all regions saw double-digit increases in time spent on video games as of June 2020, with gamers in Latin America spending 52% more time on video games and Asia Pacific spending 42% more time playing [5]. Players feel less alone and happier overall when they play video games during blockades. Positive feelings were expressed in particular by online multiplayer players during the blockade.

Despite all the data and reports showing the strong momentum of the gaming industry in the early days of the epidemic and the months that followed, this paper also has to acknowledge the pullback of the entire gaming industry after 2021. The worldwide games and services market are anticipated to shrink 1.2 percent yearly to $188 billion in 2022, while game sales will begin to decrease annually for the first time in years, according to market research firm Ampere Analysis. “After two years of huge expansion, the games market is poised to hand back a bit of that growth in 2022 as multiple factors combine to undermine performance,” said Harding-Rolls [6]. In fact, video game spending in 2022 continues to decline. According to a report by the NPD Group, spending in the second quarter of 2022 has fallen by 13 percent compared to the same period last year [7]. Although the war between Russia and Ukraine did have an impact on the overall development of the gaming industry, excluding other factors such as supply chain bottlenecks and accelerating inflation, the impact of the pandemic on the gaming industry in the long term is still worth analyzing and studying. It is important to note that even in the relatively short time since the outbreak started, the postponement or cancellation of some events has had a detrimental effect on the gaming industry, particularly when significant trade events like E3 2020 were affected, which can affect the relationships between smaller developers and publishers. Numerous eSports leagues have been forced to alter their schedules, switch from live to remote play, or even cancel matches entirely. The existence of these elements highlights the intricacy of the epidemic's effects on the gaming sector.

This paper focuses on the relationship between the fluctuation of the stock value of the gaming industry and the new cases of domestic sensitization, and the new cases of overseas infection. By developing a system that covers all three variables—the stock price of the gaming sector, the number of extra instances in China, and the number of cases elsewhere—a VAR model was developed to make it easier to analyze these variables. Impulse response plots are then plotted to very visually represent the interaction between the variables over time. The study begins to concentrate on stock price volatility, which highlights the risk associated with stock prices and industries, in the latter section of the article and develops an ARMA-GARCH model. The study pays close attention to the outcomes of the GARCH component and offers conclusions based on the model's performance in light of the conditional heteroskedasticity observed in the stock price series.

# 2. Research Design

## 2.1 Data Source

Daily new confirmed cases in China used in this paper come from National Health Commission of the People's Republic of China [8]. China was the first country to have an outbreak, and detailed data on cumulative cases have been reported daily since January 2020. These data have greatly assisted us in analyzing the outbreak in that country.

Daily new confirmed cases in China used in this paper come from the World Health Organization [9]. The World Health Organization (WHO), a specialized agency of the UN in charge of global public health, has contributed significantly to the advancement of public health worldwide. Following the COVID pandemic, WHO was the first to develop and continuously update comprehensive statistics for various nations and regions, enabling millions of people all over the world to track the progress and development of the pandemic.

The game industry indices in this article are from Choice Financial Terminal [10], an investment management and financial data analysis tool from Oriental Fortune, which provides financial institutions, academic research institutions and professional investors with high-quality financial data and related services. The terminal offers Excel, a quantitative interface, portfolio management, and other application tools, integrating information inquiry, statistical analysis, and application. It covers stocks, fixed income, funds, commodities, foreign exchange, macro industry, and other disciplines. In this paper, the end price after adjustment is chosen. Since stock prices change only on trading days, this paper omits the confirmation case data on non-trading days and classifies and renumbers the remaining data by date, matching the confirmation case data to the stock price data. In this study, Stata was the most used tool to address the problems encountered in the further exploration.

## 2.2 Unit Root Test

The unit root test determines whether a time series variable has a unit root and is non-stationary. Most quantitative analysis of time series presupposes that the series is stationary. Therefore, it is important to check the stationarity condition of the data before starting the study. This paper needs to find possible ways to improve the results if any series is not stationary.

When doing the Unit Root Test, this part assumes that the time series $xt$ can be written as:

$$x_t = c_t + \beta x_{t-1} + \sum_{i=1}^{p-1} \phi_i \, \Delta x_{t-i} + \varepsilon_t \tag{1}$$

The null hypothesis of the test is that the coefficient $\beta = 1$, which indicates that the series has a unit root and is not stationary, while the alternative hypothesis is that $\beta < 1$, indicating the series under test is stationary.

The test results for both the processed series and the raw data are shown in Table 1:

**Table 1.** ADF test

| Variables | t-statistic | p-value |
|---|---|---|
| | Online game | |
| Index | -4.7530 | 0.0006*** |
| Yield | -17.2090 | 0.0000*** |
| | Covid-19 pandemic: newly confirmed cases | |
| China | -4.4520 | 0.0018*** |
| Overseas | -12.3960 | 0.0000*** |

Note: ***, **, and * indicate the level of significance of 1%, 5%, and 10%, respectively.

This paper directly uses the logarithm original series of the game industry index. The logarithm series of game industry return, the logarithm series of Chinese new confirmation cases and the logarithm series of overseas new confirmation cases are all significantly stationary at 99% confidence intervals. Based on these results, the following model can be built with these stationary series in this paper.

## 2.3 VAR Model Specification

Sims initially officially presented the Vector Autoregression Model (VAR) in 1980 [11]. It is a methodology for examining how several time series relate to one another throughout time. The VAR model integrates these variables into a unified system, without making a distinction between endogenous and exogenous variables, and forecasts this multivariate time series as a whole based on the concept that every variable is influenced by other factors in the group.

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.

$$X_t = \sum_{i=0}^{p} \prod i \cdot X_{t-i} + U_t \tag{2}$$

Where Xt denotes a $N\times 1$ time series and Ut denotes a random error column vector.

A VAR(p) model can be expressed as follows in this scenario with three variables (stock yield, China case, and overseas case):

$$y_t=\Gamma_0+\Gamma_1 y_{t-1}+ +\Gamma_p y_{t-p}+\varepsilon_t \tag{3}$$

Where $y_t$ refers to the three response variables in this system. $\Gamma_0$, $\Gamma_1$, ..., $\Gamma_p$ are the coefficient matrix for corresponding terms. $\varepsilon t$ is the error term matrix in period $t$.

## 2.4 ARMA-GARCH Model Specification

Engle initially introduced the ARCH (autoregressive conditionally heteroscedastic) model in 1982 [12], which is used to explain a fluctuating, potentially volatile variance. The variance represents the asset risk of real-world market data, and the variance fluctuates as risk varies from period to period. The ARCH model uses an autoregressive logic that is similar to the AR model to forecast future variance: if the variance of the time series in the previous period is high, then the variance in the following period may also be high. Typically, the $ARCH$ (1) model can be written as:

$$Var(y_t|y_{t-1}) = \sigma^2 = \alpha_0 + \alpha_1 y_{t-1}^2 \tag{4}$$

The variance at time $t-1$ is related to the variance at time $t$. A relatively large value of $y_{t-1}^2$ gives a relatively large value of the variance at time t. This means that the value of $y_t$ is less predictable at time $t-1$ than at times after a relatively small value of $y_{t-1}^2$.

An $ARCH(p)$ model can be written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_p\varepsilon_{t-p}^2 \tag{5}$$

where $\sigma t$ is the anticipated timeframe variance in period $t$. $\varepsilon t$ refers to the actual variance in period $t$. $\alpha_0$ is constant.

By including a GARCH term to the original ARCH model, Bollerslev improved it with a generalized ARCH (GARCH) model in 1986 [13]. In order to model variation through time, the GARCH (generalized autoregressive conditional heteroskedasticity) model uses previous squared observations and past variances. For instance, GARCH (1,1) is:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \tag{6}$$

This can be considered as $ARCH$ (∞) model. GARCH (1,1) with three terms can be written as:

The return of the market is positively correlated with its risk. An ARMA-GARCH model was created to examine the volatility of stock returns in the gaming industry in order to mitigate market risk. Two value and variance equations make up the ARMA-GARCH model. Although the ARMA part also analyzes the value, the GARCH part shows more conclusions about the risk.

## 3. Empirical Result

### 3.1 VAR Model Result

Three stationary series are introduced into our Vector Autoregression system in this section of the paper: the logarithmic stock yield, the logarithmic freshly increasing confirmed case in China, and the logarithmic overseas case. First, this part uses LR method to determine the maximum lag order k. To illustrate, For

$$LR = -2(logL_k - logL_{k+1}), LR \sim X^2_{(N^2)} \tag{7}$$

N denotes number of variables with interaction and k denotes how many lagged variables are needed to explain the endogenous variables that are interacted.

The lag order of the VAR model is considered to be moderate when the LR statistic is less than the critical value. When the LR statistic is greater than the critical value, the lag order of the VAR model is considered not yet high enough, and it is necessary to continue adding more lagged variables as explanatory variables. The right order p for this VAR(p) model is chosen in Stata using several VARSOC selection-order criteria.

Table 2 indicates that a VAR model with 12 orders is considerable.

**Table 2.** VAR model identification

| Lag | LL | LR | df | p | FPE | AIC | HQIC | SBIC |
|---|---|---|---|---|---|---|---|---|
| 0 | -1237.88 | | | | .025567 | 4.84719 | 4.85692 | 4.87202 |
| 1 | -735.488 | 1004.8 | 9 | 0.000 | .003721 | 2.91987 | 2.95881 | 3.01921 |
| 2 | -677.757 | 115.46 | 9 | 0.000 | .003076 | 2.72952 | 2.79766 | 2.90336 |
| 3 | -656.36 | 42.793 | 9 | 0.000 | .002931 | 2.68656 | 2.77844 | 2.92943 |
| 4 | -633.4 | 45.919 | 9 | 0.000 | .002775 | 2.62656 | 2.75312 | 2.94941 |
| 5 | -399.103 | 468.59 | 9 | 0.000 | .001151 | 1.7465 | 1.90226* | 2.14384* |
| 6 | -396.854 | 4.4987 | 9 | 0.876 | .001182 | 1.77287 | 1.95783 | 2.24471 |
| 7 | -385.468 | 22.772 | 9 | 0.007 | .001171 | 1.76355 | 1.97771 | 2.30989 |
| 8 | -352.652 | 65.632 | 9 | 0.000 | .001067 | 1.67051 | 1.91389 | 2.29136 |
| 9 | -350.956 | 3.3921 | 9 | 0.947 | .001098 | 1.69905 | 1.97162 | 2.3944 |
| 10 | -334.623 | 32.666 | 9 | 0.000 | .001067 | 1.6704 | 1.97218 | 2.44025 |
| 11 | -332.044 | 5.157 | 9 | 0.820 | .001094 | 1.69548 | 2.02647 | 2.53984 |
| 12 | -306.946 | 50.196* | 9 | 0.000 | .001028* | 1.6326* | 1.99279 | 2.55146 |

After building the model of $VAR$ (12), a tool in Stata codenamed varstable is used to check the stability condition of the eigenvalues after vector autoregressive parameter estimation, which will draw a unit circle to visualize the results. The VAR estimates are said to be stable if all the points denoting the eigenvalues fall inside the unit circle. Here in Figure 1, all the points are strictly inside the circle, which means the stability condition is satisfied.

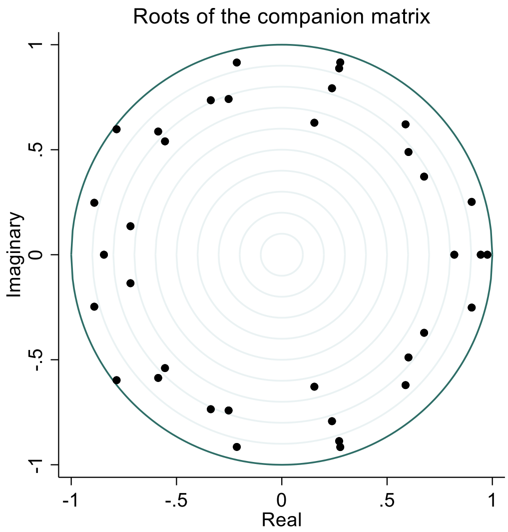


**Figure 1.** VAR stability

Photo credit: Orginal

## 3.2 Impulse Response

Figure 2 displays the findings of the impulse response for stock returns in the gaming industry. From the impulse response estimates, a 1% increase in the number of new confirmations in China in period t=0 has a positive effect on the online game industry returns in future periods, with a maximum net effect of about 0.25%. After this period the effect turns negative. Overall, the positive and negative effects largely cancel out. Similarly, the impact of a 1-unit new overseas confirmed shock on the online game industry is also positive in future periods, with a maximum positive effect of about 0.1%. Overall, the net effect is positive. In terms of the time effect, the shock in period t=0 gradually decays to zero after 20 periods.

Impulse: Newly confirmed cases, China Impulse: Newly confirmed cases, overseas

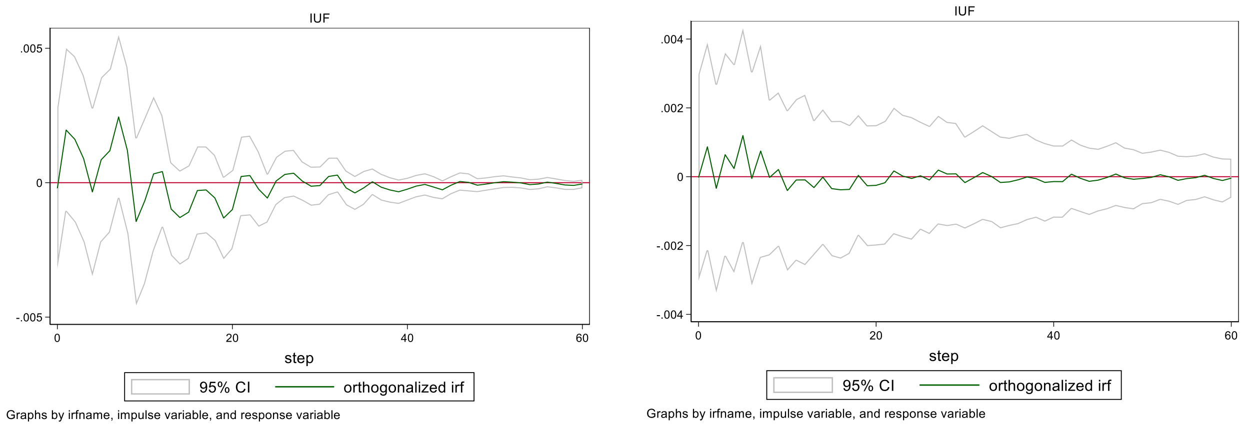


**Figure 2.** Impulse and response

Photo credit: Orginal

## 3.3 ARMA-GARCH Order Selection

Check the partial autocorrelation plot (PACF plot) and Autocorrelation Plot (ACF Plot) of Figure 3 shows the results of the analysis of the series in Stata. The delays 1 and 4 terms of the original series may have a major impact on the present data, and the black rectangle is a benchmark for finding statistically significant terms in the ARMA-GARCH model.

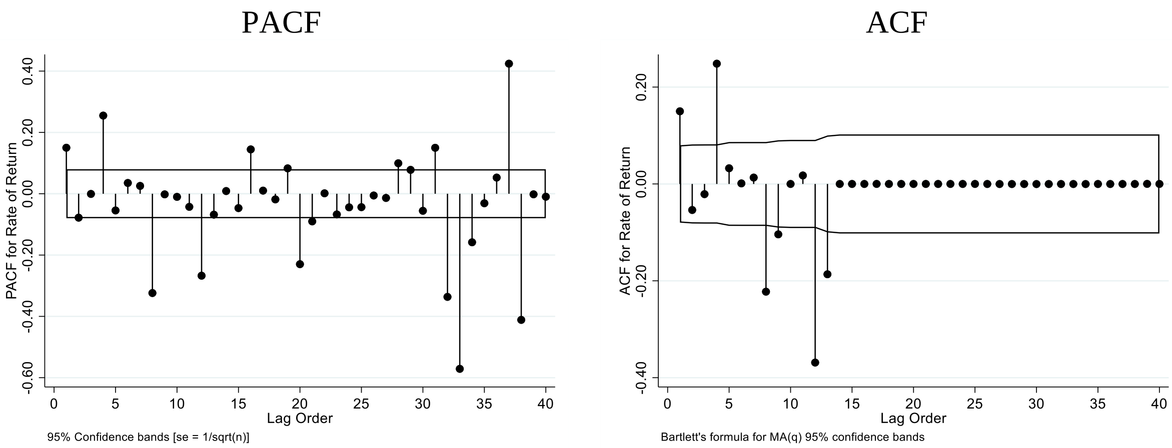


**Figure 3.** PACF and ACF

Photo credit: Orginal

### 3.4 ARMA-GARCH Model Result

This part uses the ARMA (3,1)-GARCH (1,1) model and train the model with exogenous lagged terms from domestic or overseas cases. This paper focuses more on the variance equation of the GARCH component and focuses on whether the severity of the COVID-19 situation leads to changes in the volatility of stock returns in the gaming industry.

From the estimation results of the ARMA-GARCH model (Table 3), both the ARCH term and the GARCH term of online game returns are statistically significant, indicating that there is significant aggregation of returns in the online game industry, which allows for GARCH modeling.

From the external explanatory variables, the coefficients of new confirmations in China and overseas are 4.0659 and 3.3579, respectively, which means that a 1% increase in the number of new confirmations in both is associated with a 4.0659 unit and 3.3579 unit increase in the volatility of the game industry returns, respectively, and the coefficients are significant at the 1% level.

**Table 3.** ARMA-GARCH estimation results

| | (1) | | (2) | |
|---|---|---|---|---|
| | Coefficient | Std. err | Coefficient | Std. err |
| Newly confirmed cases, China | 4.0659$^{***}$ | 0.1756 | | |
| Newly confirmed cases, overseas | | | 3.3579$^{***}$ | 0.0231 |
| ARCH (-1) | 0.0592$^{***}$ | 0.0023 | 23.0290$^{***}$ | 2.5167 |
| GARCH (-1) | 0.7810$^{***}$ | 0.0024 | 0.0711$^{***}$ | 0.0029 |
| Constant | -35.5349$^{***}$ | 0.0930 | -52.8664$^{***}$ | 0.3158 |

## 4. Discussion

This paper finds that stock returns in the gaming industry are dramatically affected by new cases of novel coronaviruses in the short term, with a positive effect at the beginning and then turning negative. In the long run, stock returns in the gaming industry are still positively correlated with new cases of novel coronavirus. However, in the environment of a normalized epidemic, investor panic is no longer so severe that the impact on gaming industry returns is quantitatively insignificant. Therefore, epidemic cases become no longer a significant predictor of the future stock price.

Much of the existing literature refers to the explosive growth of the gaming industry in the early stages of the outbreak, which stemmed largely from the psychological need for people with restricted mobility. These findings coincide with the results obtained from the impulse plots in this paper and the findings of the ARMAR-GARCH model. Unlike most papers, the model in this paper provides a more in-depth analysis of the long-term effects of the epidemic. At one point in the latter part of 2021 and into 2022, stock yields in the gaming industry plummeted, which I believe was a counterbalance to the market's overreaction to the stock market in the early stages of the outbreak. As illustrated in the impulse response plots in this work, the response of impulse from the recently proven case in China is an instantaneous increase and then a sharp reduction in stock yield. Then, it will make a convergence to maintain stability at a distance of roughly 20 lags.

According to the ARMA-GARCH model, new confirmed diagnoses in China and new confirmed diagnoses overseas both enhance yield volatility in the short run. In the long run, the increase in cases still does not trigger price volatility. Newly confirmed cases within China have a greater impact on stock price volatility than overseas cases. This coincides with the relationship between trading volume and stock price volatility proposed by Girard E., Omran M in 2009 [14]. The trading volume in overseas markets is more enormous compared to the Chinese market and, accordingly, more resistant to yield volatility, receiving relatively less volatility from the epidemic. When a pandemic breaks out, the gaming industry receives a positive impact in the short term and the trading volume rises leading to higher return volatility, which is in line with the study by G Chen, M Firth, and OM Rui in 2001 [15].

## 5. Conclusion

The outbreak of Newcastle pneumonia in early 2020 caused turmoil in global financial markets. In the short term after the rapid spread of the outbreak in China, the U.S. and Europe, investors panicked and the risk aversion of capital led to a massive "flight to safety" from financial markets, which led to a precipitous decline in financial market indices. Among them, a few industries were spared, and the online game industry was one of them, and there was a great favorable market in the industry in the short term, and the market also reacted to this information. For a short period of time the gaming industry saw a surge, yet after 2021, there was another plunge. This paper examines the impact of newly confirmed cases globally and regionally on the stock returns of the gaming industry and the impact caused by stock return volatility. The findings show that outbreaks are positively correlated with stock returns and amplify stock volatility.

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