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Empirical study and model simulation of global stock market dynamics during COVID-19

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Abstract

At the beginning of 2020, COVID-19 swept the world and changed various aspects of human society, such as economy and finance, life and health, migration and population. We first empirically study how the dynamic behaviors of stock markets are affected by COVID-19, and focus on the large volatility dynamics, variation-fluctuation correlation function and epidemic-fluctuation correlation function. Then we generalize the Heston model to simulate the global stock market dynamics, and an epidemic index computed from empirical data is directly taken as the external force in the modelling.

1. Introduction

In March 2020, the World Health Organization (WHO) declared that COVID-19 could be characterized as a pandemic. The outbreak of the epidemic has scientifically attracted the attention of scholars in various fields. Based on the epidemic model, government intervention policies and complex social networks have been introduced to investigate the spread of the epidemic and predict the trend of the epidemic [1–6]. In fact, the epidemic has significantly changed people’s lives in many aspects, such as health, transportation, catering service and economy etc. [7–9]. Financial markets exhibit the fastest response at the state level [10–12].

After COVID-19 spread worldwide, the financial markets experienced strong fluctuations. For example, the U.S. stock markets collapse significantly with the S&P 500 index dropping 20% in March 2020. The outbreak of COVID-19 has an impact on the oil price, exchange rate, and cryptocurrencies [13–18]. The epidemic elevates the volatility of the oil markets and intensifies the correlation between the oil markets and the U.S. stock markets [13,14]. The outbreak also affects the spillover of the RMB exchange rate, and enhances the relationship between the exchange rate of the Japanese Yen and the stock markets [15,16]. The cryptocurrency markets reduce the self-similarity and the efficiency due to COVID-19 [17,18].

Furthermore, the emergence of COVID-19 strengthens the economic policy uncertainty and the geopolitical risks [19–22]. The financial markets exhibit heterogeneous behaviors towards socio-economic and political announcements on the epidemic, and a positive-negative asymmetry towards news about the epidemic [21,22]. Moreover, the complex network structure of the global financial markets is analyzed [23–25]. There is a drastic reduction in connectivity among countries after the outbreak in the trade network, but not in the stock network. COVID-19 leads to a close relation of the stock markets among countries [24,25]. Besides, COVID-19 in 2020 has been compared with the global financial crisis in 2008 [26,27], and the European and U.S. markets are more influenced by COVID-19 than the Asian markets [26].

In these previous studies, the epidemic effect on the financial markets is explored from some specific aspects, such as the currencies, the economic policies, and the complex networks of the global markets. In this paper, we focus on the fundamental dynamic behavior of the stock markets, in particular, the specificity of the large-volatility dynamic in 2020, the impact of COVID-19 on the leverage effect, and the correlation between the epidemic and the stock market dynamics. Based on the empirical data, we investigate the large fluctuations induced by COVID-19 in 2020 and their dynamic effects, compared with those in the past 10 years. Due to different economic and medical levels,
the epidemic effect on stock markets may vary from country to country. Therefore, it is very important to quantify the epidemic effect on stock markets through computing the correlation function between the epidemic index and the stock price.

In addition to the empirical analysis, the model simulation is also an important approach to investigate the epidemic effect on the financial markets. The econometric models are used to study the impact of COVID-19 on stock market returns and volatilities [28–30], and the deep learning models are applied to analyze the commodity prices [31]. Incorporating information about the epidemic improves the performance of forecasting the abnormal stock prices [32,33]. In this paper, we generalize the well-known Heston model to simulate the stock market dynamics under the influence of COVID-19, and explain the empirical findings from the real market data. An epidemic index computed from empirical data is introduced in the generalized Heston model as the external force.

32 stock markets are selected to investigate the dynamic behaviors during COVID-19. We compute the remnant volatility and the variation-fluctuation correlation function. Further, the correlation function between the epidemic and fluctuation is introduced to quantify the impact of COVID-19 on the stock market dynamics.

The structure of the paper is as follows. Data and methods are described in Section 2. The empirical analysis is presented in Section 3. The generalized Heston model is simulated in Section 4. The conclusion comes in Section 5.

2. Data and methods

2.1. Data

The stock market data and epidemic data from 32 countries worldwide are collected, respectively from the websites https://cn.investing.com and https://github.com/owid/covid-19-data. The stock market indexes are listed in Table 1, and the 32 countries are classified into four global regions, i.e., Asia & Pacific, Europe & North America, Latin America and Africa. The daily closing price of the stock market index is denoted by \( Y(t) \). Then, the dynamic variable is defined as the variation of \( Y(t) \) in a unit time step, \( R(t) = \ln Y(t) - \ln Y(t - 1) \), which is called the return. A simple quantity for describing the fluctuation is the absolute return \( \nu(t) = |R(t)| \), the so-called volatility.

2.2. Remnant volatility

To study the dynamic relaxation after a large volatility, we introduce the remnant volatility,

\[
\nu_r(t) = \langle |Z| \rangle /Z,
\]

where \( \langle \cdot \rangle \) represents the average over those \( t \) with specified large volatilities, and \( Z = \langle |R(t)| \rangle \). \( \nu_r(t) \) is the average volatility. The remnant volatility \( \nu_r(t) \) describes how the dynamic system relaxes from a large volatility to the stationary state. In our analysis, the large volatilities are selected by the condition \( |R(t)| \gg \xi \), and the threshold \( \xi \) is well above \( \nu \), e.g., \( \xi = 3 \nu \). For reducing the fluctuations, we introduce the cumulative function

\[
V_r(t) = \sum_{t'=0}^{t} \nu_r(t').
\]

\( V_r(t) \) and \( V_r(t) \) may approximately obey a power-law-like behavior up to a certain time period, since large shocks in volatilities are usually followed by a series of aftershocks [34]. Thus the cumulative function \( V_r(t) \) could be written as \( V_r(t) = t^p \), with \( p \) being the exponent, and this is one of the characteristics of the stock market dynamics.

2.3. Variation-fluctuation correlation function

The variation-fluctuation correlation function is defined as

\[
L(t) = \frac{\langle (R(t) \cdot |R(t') + t|^2) \rangle - \langle R(t') \rangle \cdot \langle |R(t')|^2 \rangle}{L_0},
\]

where \( \langle \cdot \rangle \) represents the average over time \( t \), and \( L_0 = \langle |R(t')|^2 \rangle \). For \( t > 0 \), \( L(t) \) describes the correlation between the past variation \( R(t') \) and the future fluctuation \( IR(t') + t \). The phenomenon of a negative \( L(t) \) is called the leverage effect. In Ref. [35], it is shown that large volatilities dominate the variation-fluctuation correlation in the stock market dynamics. In other words, the leverage effect is more pronounced during the periods with large fluctuations. Therefore, the leverage effect after the outbreak of COVID-19 reflects the epidemic impact on the stock markets.

2.4. Correlation between COVID-19 and stock market dynamics

We denote the daily number of new confirmed COVID-19 cases in each country with \( N(t') \). Occasionally, the government revised the number of the confirmed cases, resulting in a negative value. For simplicity, these negative data are set to zero. In Spain, the data of the new confirmed COVID-19 cases released on Monday are aggregates of the whole weekend. To compensate for the weekend effect, we uniformly distribute the confirmed cases reported on Monday to the past three days. Due to different outbreak times and national conditions in different countries, it is not that comprehensive to directly use \( N(t') \) for describing the severity of the epidemic in each country. On the other hand, the auto-correlation of \( N(t') \) is rather strong, with a correlating time about two or three weeks. Thus we construct an epidemic index,

\[
I(t') = \frac{N(t')}{N_r(t')},
\]
where $N_{\text{c}}(t')$ is the average number of the confirmed cases in the past $\tau$ days, and $\tau = 14$ is reasonably set to reflect the background epidemic [36]. In other words, the epidemic index $I(t')$ describes the temporal variation of the new confirmed cases compared to the background epidemic. In subsequent calculations, the non-trading days will be ignored, and $t'$ represents only the trading day. Then, the epidemic-fluctuation correlation function is defined as

$$
C(t) = \langle I(t') \cdot |R(t' + t)| \rangle - \langle I(t') \rangle \cdot \langle |R(t' + t)| \rangle.
$$

The impact of the epidemic on a stock market can be quantified through $C(t)$ under a certain time window [36,37].

3. Empirical analysis

The empirical analysis for the 32 countries is mainly presented through four global regions, Asia & Pacific, Europe & North America, Latin America, and Africa. From the returns $R(t')$ and the volatilities $\nu(t')$ over the past decade, we obtain the probability distribution $P(R)$ of the returns and the cumulative function $V_c(t')$ of the remnant volatility in each country, and then average over the countries in the four regions respectively. To reveal the characteristics of the stock market dynamics driven by COVID-19, we particularly draw the results in 2020, compared to those from 2011 to 2019. As examples, the probability distribution $P(R)$ of returns is shown for Asia & Pacific and Europe & North America in Fig. 1(a) and (b) respectively. The central peak of $P(R)$ in 2020 is significantly lower than that from 2011 to 2019. In other words, the volatilities in 2020 are larger. The result is similar for Latin America, but not for Africa. The probability distribution of returns in Africa does not show a lower peak in 2020.

As shown in Fig. 1(c) and (d), the cumulative function $V_c(t)$ of the remnant volatility in 2020 increases much more dramatically than that from 2011 to 2019, and the exponent $p$ is about two times larger. These results indicate that the aftershocks of the large fluctuations caused by COVID-19 are significantly stronger, and the dynamic effect of COVID-19 is rather particular. For Latin America and Africa, such a phenomenon is also detected, although the probability distribution $P(R)$ of returns for Africa is not different from that of the normal years. By definition, the probability distribution $P(R)$ reflects the overall volatilities, while the cumulative function $V_c(t)$ of the remnant volatility describes the time correlation of the large fluctuations. Compared with other regions, the epidemic of COVID-19 in Africa is less severe, but still resulting in a larger exponent $p$ than from 2011 to 2019.

The impact of COVID-19 on the stock market dynamics is also observed in the variation-fluctuation correlation function $L(t)$, as shown in Fig. 2. We calculate the correlation function respectively in four time periods, namely 2011 to 2014, 2013 to 2016, 2015 to 2018, and 2017 to 2020. For the three time periods without the epidemic in 2020, only a rather weak leverage effect is observed. For the time period from 2017 to 2020, the leverage effect is significantly enhanced, and the maximum magnitude of $L(t)$ is a few times larger. But this phenomenon is not evident in Africa, since it is far less affected by COVID-19 than in other regions.

To investigate more explicitly the epidemic effect on the stock markets, we divided the first year of COVID-19 into three four-month periods: (i) from March to June 2020; (ii) from July to October 2020; (iii) from November 2020 to February 2021. The epidemic-fluctuation correlation function $C(t)$ for the four regions is shown for different time periods in Fig. 3. At the early stage of the outbreak, i.e., the first time period, the stock markets of Europe & North America and Latin America exhibit a significant positive correlation, while the positive correlation is slightly weaker for Asia & Pacific. The countries in Asia, such as China, Japan, and South Korea, were the first to be hit by COVID-19 in early 2020, and the epidemic was successfully controlled afterwards. When COVID-19 entered the global pandemic, China was already planning to resume normal life and work.

As for Africa, the epidemic effect on financial markets is weaker than elsewhere, even in the early stage of the outbreak. The lower COVID-19

![Fig. 1.](image-url) (a)-(b) The probability distribution $P(R)$ of returns, (c)-(d) the cumulative function $V_c(t)$ of the remnant volatility. The blue circles represent the average from 2011 to 2019, and error bars are calculated within the nine years. The exponent $p$ is estimated from the slope of the cumulative function $V_c(t)$ in double-log coordinates. The large volatilities are selected by the condition $|R(t')| > \zeta$, with $\zeta = 3\sigma$, and $\sigma$ is the average volatility.
Fig. 2. The variation-fluctuation correlation function $L(t)$ for the four global regions in different time periods.

Fig. 3. The correlation function $C(t)$ between COVID-19 and the stock market dynamics in different time periods.
burden in Africa is explained from several perspectives, one of which may be the shape of the Africa’s population pyramid [38]. The public panic and mortality burden is mainly caused by the elder with underlying medical conditions, while Africa has the youngest population among the world. The epidemic did not cause a great panic in Africa, thus the correlation between COVID-19 and the stock dynamics is absent.

From an economic intuition point of view, COVID-19 is a black-swan event that was new and unforeseeable, causing panic among people and strong fluctuations in financial markets. After the epidemic entered the global pandemic, the governments adopted city closures and travel bans etc., the epidemic was globally controlled to a certain extent. On the other hand, many countries have made great efforts to develop COVID-19 vaccines, which reduced the public fear [39]. In particular, China, the country with the earliest outbreak, basically returned to the normal life within four months. Therefore, the correlation between COVID-19 and the stock dynamics essentially diminished after June 2020.

4. Model

In 1993, Heston proposed a stochastic volatility model to price options [40]. The specific form of the model is as follows

\[
\begin{align*}
\text{d}Y_t &= \mu Y_t \text{d}t + \sqrt{V_t} Y_t \text{d}W^1_t, \\
\text{d}V_t &= a(b - V_t) \text{d}t + c\sqrt{V_t} \text{d}W^2_t,
\end{align*}
\]

where \(Y_t\) describes the stock price at time \(t\), \(V_t\) denotes the volatility of the stock price, \(\mu\) is the risk-free rate, \(a\) and \(c\) are respectively the mean reversion of \(V_t\), the long-run variance of \(V_t\), and the amplitude of volatility fluctuations. \(W^1_t\) and \(W^2_t\) define two correlated Weiner processes with a correlation coefficient \(\lambda\), and \(\text{d}W^1_t\text{d}W^2_t = \lambda \text{d}t\).

The coherent resonance phenomenon of the stock returns and volatilities can be investigated with the Heston model, and the herd behavior of the stock prices influenced by the time delay can also be explored by the delayed Heston model [41–43]. In addition, it is argued that the leverage effect could be explained in terms of a wide class of correlated stochastic volatility models, such as the Heston model [44]. In this work, we introduce a generalized Heston model to simulate the dynamic behaviors of the stock markets during COVID-19.

Due to the sudden outbreak of COVID-19, the stock markets are exposed to exogenous risks. The random noise \(W^2_t\) in the Heston model cannot produce the large fluctuations caused by the epidemic. Therefore, we generalize the Heston model by taking into account the epidemic effect to describe the dynamic behavior during COVID-19, and rewrite Eq. (7) to

\[
dV_t = a(b - V_t) \text{d}t + c\sqrt{V_t} \text{d}W^2_t + \xi \text{d}L_t,
\]

where \(L_t\) denotes the epidemic index \(L(t)\) introduced in Eq. (4), \(\xi\) represents the scale of the epidemic impact. Before the epidemic outbreak in that country, we set \(\xi = 0\). Then the generalized Heston model is reduced to the Heston model.

By selecting appropriate parameters and giving the epidemic index \(L_t\), the generalized Heston model may simulate the returns and volatilities of each country’s stock market, both before and after the outbreak of COVID-19. From the simulation results, we can calculate the probability distribution \(P(R)\) of returns, the cumulative function \(V_\ast(t)\) of the remnant volatility, the variation-fluctuation correlation function \(L(t)\), and the epidemic-fluctuation correlation function \(\xi(t)\).

Taking Europe & North America as an example, the simulation results of the generalized Heston model are shown in Fig. 4, in comparison with the empirical results. In Fig. 4(a), the probability distribution \(P(R)\) of the returns in 2020 from the generalized Heston model is presented. The simulation obviously yields a lower central peak of \(P(R)\) consistent with that of the empirical one in 2020. According to the empirical results, a positive-negative asymmetry in the probability distribution \(P(R)\) of returns is observed in most years, but particularly stronger in 2020. In light of the risks posed by the pandemic to economic activities, the Federal Reserve System decided to lower the target range for the federal funds rate, which led to a bull market in the second half of

![Fig. 4. Simulation results of the generalized Heston model for Europe & North America, compared with the empirical ones. (a) The probability distribution \(P(R)\) of returns, (b) the cumulative function \(V_\ast(t)\) of the remnant volatility, (c) the variation-fluctuation correlation function \(L(t)\), (d) the correlation function \(\xi(t)\) between COVID-19 and the stock market dynamics.](image-url)
2020. Due to the government policy intervention, a zero risk-free rate $\mu$ is not sufficient to capture the peculiarity in 2020. Therefore, we set a non-zero risk-free rate $\mu$ for each country, which is about 0.6–0.7. Moreover, as shown in Fig. 4(b), the cumulative function $V_\gamma(t)$ of 2020 from the simulations nicely agrees with the empirical one. Here one must note that the standard Heston model could not simulate the dynamic behavior associated with large volatilities, such as the cumulative function $V_\gamma(t)$ of the remnant volatility, even in the period without COVID-19 from 2011 to 2019. In general, it needs to input the external forces to describe the large fluctuations.

As shown in Fig. 4(c), the simulation well reproduces the strength of the leverage effect, and the trend of the correlation function in the time period from 2017 to 2020. Although the generalized Heston model only considers the external risk induced by COVID-19 in 2020, the simulation essentially catches the leverage effect, and it reveals that the leverage effect in this time period comes mainly from the large fluctuations caused by the global COVID-19 pandemic. The correlation between the epidemic index $I$ and the simulation volatility from March to June 2020 is shown in Fig. 4(d), qualitatively in agreement with the empirical result. Due to the government intervention, the daily number of new confirmed COVID-19 cases tended to be stable after June 2020. The epidemic index $I$ decreases over time and eventually fluctuates around 1. In other words, the epidemic effect $\xi(I - 1)$ in the generalized Heston model weakens to be around zero. Therefore, the correlation between the epidemic and financial markets decays to zero over time.

To summarize, the characteristic dynamic behaviors induced by COVID-19 as displayed in Fig. 4 can be fully simulated just through introducing the epidemic index computed from the empirical data as the external force in the generalized Heston model. This is a great success.

5. Conclusion

COVID-19 has essentially influenced the dynamic behaviors of the stock markets after it entered the global pandemic in March 2020. Empirical results of the remnant volatility of large fluctuations and the variation–correlation function show the specificity of the stock market dynamics in 2020 and the difference among the four global regions. The outbreak of the epidemic significantly increases the remnant volatility and intensifies the leverage effect, but it is exceptional in Africa. The risk posed by COVID-19 to the stock markets has diminished over time. To simulate the dynamic behaviors of the stock markets with COVID-19, we generalize the Heston model by taking the epidemic index $I$ computed from the empirical data as the external force. The generalized Heston model successfully reproduces the dynamic behaviors caused by COVID-19.

CRediT authorship contribution statement

Lifu Jin: Conceptualization, Software, Visualization, Writing – original draft.
Bo Zheng: Conceptualization, Methodology, Formal analysis, Supervision, Writing – review & editing, Funding acquisition.
Jiahao Ma: Data collection, Software, Validation.
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Long Xiong: Conceptualization, Formal analysis.
Xiongfei Jiang: Conceptualization, Methodology, Writing – review & editing, Funding acquisition.
Jiangcheng Li: Methodology, Writing – Review & editing.

Declaration of competing interest

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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