Analysis of 2020 Global Stock Market Crash

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Abstract
We applied the Log-periodic power law singularity (LPPLS) methodology to analyze the performances of the 10 major global stock market indexes from both developed and emergent stock markets in the 2020 global stock market. The results show that the crashes for the 7 indexes: SP500, DJIA, NASDAQ, DAX, CSI300, BSESN, and BOVESPA, are endogenous due to the increasingly systemic instability of the financial markets, while the crashes in the three indexes: FTSE, NIKKEI, and HSI, are exogenous caused by external shocks.

Key Words: 2020 stock market crash, Log-periodic power law singularity (LPPLS), Financial bubble, Market crash.

1. Introduction

Beginning on February 20, 2020, the global stock markets had turned the regime from a bull market to bear market, as shown in Figure 1. In the ensuing five weeks, the three major U.S. stock market indexes: the S&P 500 (SP500), the Nasdaq Composite (NASDAQ), and the Dow Jones Industrial Average index (DJIA), fell sharply by 33.9%, 30.1% and 37.1%, respectively. This was the worst decline since the Great Recession in 2008 and interrupted the bull market trend of the past 11 years from March 2009 to February 2020.

Many people believed that the root cause of the 2020 stock market crash is exogenous, such as, the COVID-19 pandemic-induced market instability, corporate debt bubble, recession fears, market liquidity crisis, mass hysteria, breakeven oil prices, etc. In general, the causes of crashes can be divided into two types: endogenous crash and exogenous crash. In endogenous crash, large declines in the price are caused by the factors inside the financial market, such as the dot.com crash of April 2000, while in exogenous crash, large declines in the price caused by external shocks, such as Nazi invasion of France and Belgium, Luxembourg, Netherlands on May 10, 1940.

In this study, we adopted the Log-periodic power law singularity (LPPLS) model to unveil the underlying mechanic of the 2020 global stock market by analyzing the performances of the three major U.S. stock market indexes (SP500, DJIA and NASDAQ) as well in other Western, and emergent market indexes, including the Financial Times Stock Exchange 100 Index (FTSE) for the London Stock Exchange in United Kingdom, the DAX performance index (DAX) for the Frankfurt Stock Exchange in Germany, the Nikkei Stock Average index (NIKKEI) for the Tokyo Stock Exchange in Japan, the CSI

300 stock market index (CSI300) for the Shanghai Stock Exchange and the Shenzhen Stock Exchange in China, the Hang Seng Index (HSI) for the Hong Kong Stock Exchange in Hong Kong, the BSE SENSEX index (BSESN) for the Bombay Stock Exchange in India, and the Bovespa Index (BOVESPA) for the B3 Stock Exchange in Brazil.

The LPPLS model, originating from the interface of financial economics, behavioral finance and statistical physics, defines a positive (negative) financial bubbles as a process of unsustainably super-exponential growth (decline) to achieve an infinite return in finite time, forcing a short-lived correction according to the symmetry of discrete scale invariance (Sornette, 1998). The LPPLS model can capture two distinct features normally observed in the regime of bubbles, that is, faster-than-exponential growth of the price resulting from positive feedback by imitation and herding behavior of noise traders, and the accelerating log-periodic volatility fluctuations of the price growth from expectations of higher returns or an imminent crash. Recently, the LPPLS model has been deployed to detect bubbles and crashes in a variety of financial markets, such as the stock markets (Demirer et al., 2019; Shu, 2019; Shu et al., 2021; Shu & Zhu, 2019, 2020a; Sornette et al., 2015) and the cryptocurrency market (Shu & Zhu, 2020b; Wheatley et al., 2019).

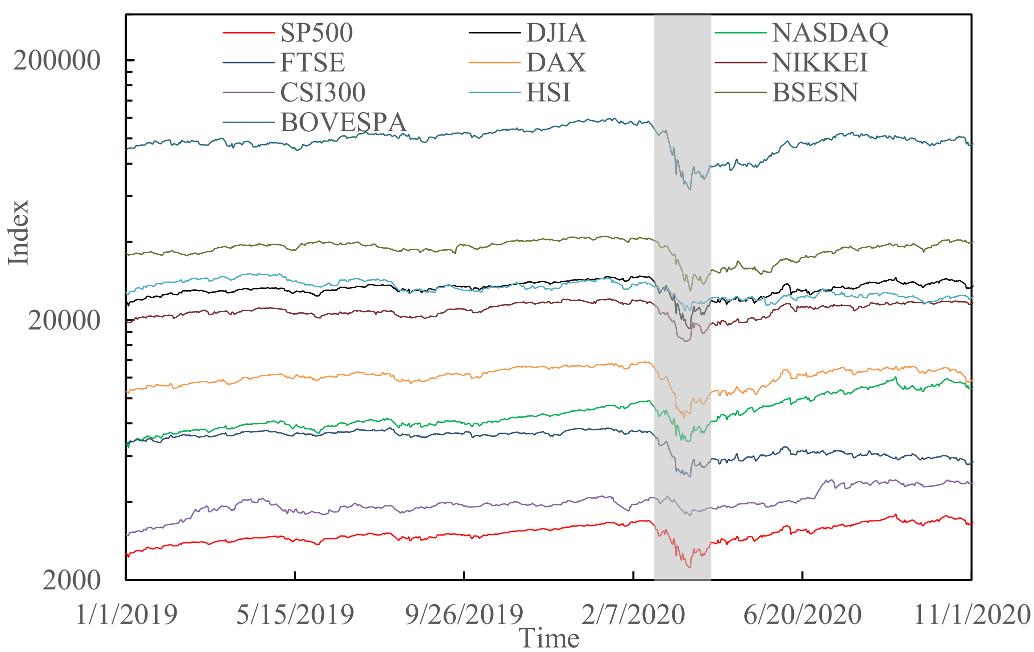


Figure 1: Evolution of price trajectories of the 10 major stock market indexes from January 2019 to November 2020 (The dark shadow box indicates the period of 2020 global stock market crash)

2. Methodology

2.1 The Log-Periodic Power Law Singularity (LPPLS) Model

The simple mathematical formula of the LPPLS can be written as (Filimonov & Sornette, 2013):

$$\mathrm{LPPLS}(t) \equiv E[\ln p(t)] = A + B(t_c - t)^m + C_1(t_c - t)^m \cos[\omega\, ln(t_c - t)] \\ + C_2(t_c - t)^m \sin[\omega\, ln(t_c - t)] \quad (1)$$

where $p(t)$ is the observed asset price, t_c is the critical time, representing the most probable time for a regime change. In addition, m is the power parameter with a range between 0 and 1 to ensure that not only the price remains finite at the t_c, but also the expected logarithmic price diverges at the t_c. Lastly, A, B, C_1 and C_2 are four linear parameters. The seven parameters $(t_c, m, \omega, A, B, C_1, C_2)$ can be estimated by calibrating the LPPLS model based on the Ordinary Least Squares method. In this study, we used the covariance matrix adaptation evolution strategy (Hansen et al., 1995) to solve this optimization problem, and adopted the search space in Equation (2) as well as the filter conditions in Equation (3) (Shu & Zhu, 2020b):

$$m \in [0,1], \omega \in [1,50], t_c \in \left[t_2, t_2 + \frac{t_2 - t_1}{3}\right], \frac{m|B|}{\omega\sqrt{C_1^2 + C_2^2}} \geq 1 \tag{2}$$

$$m \in [0.01,0.99], \omega \in [2,25], t_c \in \left[t_2, t_2 + \frac{t_2 - t_1}{5}\right], \frac{\omega}{2}\ln\left(\frac{t_c - t_1}{t_c - t_2}\right) \geq 2.5,$$
$$\max\left(\frac{|\widehat{p_t} - p_t|}{p_t}\right) \leq 0.20,\ p_{lomb} \leq \alpha_{sign}, \ln(\widehat{p_t}) - \ln(p_t) \sim \mathrm{AR}(1) \tag{3}$$

To measure sensitivity of observed bubble pattern to the time interval between the end time and the start time in the fitting windows ($dt = t_2 - t_1$), The LPPLS confidence indicator (Sornette et al., 2015) is defined as the fraction of fitting windows in which the LPPLS calibrations satisfy the specified filter conditions. A large value of the LPPLS confidence indicator indicates a more reliable LPPLS pattern. A small value of the indicator signals a possible fragility since the LPPLS pattern is presented in a few fitting windows.

2.2 Classification of Crash Types

We proposed to use the confidence indicator as a classification proxy to distinguish between endogenous crash and exogenous crash in the financial markets. This is because the LPPLS model, modeling the transient super-exponential growth of asset trajectories resulting from self-reinforcing cooperative herding and imitative behaviors through interactions between market participants involving long-term memory processes of an endogenous organization, can only detect the endogenous crashes. As a rule of thumb, a value LPPLS confidence interval greater than 5% for the daily price trajectory signals that the price process is unsustainable and bears a substantial risk for an impending critical transition, thereby the value of 5% is adopted in this study as the threshold for the daily price trajectory.

3. Bubble Identification

We collected the daily data of the 10 major global stock market indexes from both developed and emergent stock markets from Yahoo Finance (https://finance.yahoo.com/). In order to calculate the LPPLS confidence indicator, we shrunk the length of time windows $t_2 - t_1$ from 650 trading days to 30 trading days in steps of 5 trading days for each endpoint t_2, and moved the endpoint from January 2, 2019 to May 31, 2020. The value of the LPPLS confidence indicator at a given time t_2 is causal because it is estimated based only on data prior to that time. The LPPLS confidence indicators for a series of varying t_2 provide useful insights into the time development of the bubble signal.

Both the positive and negative bubbles in the stock market indexes are detected in this study. The positive bubbles are associated with the upwardly accelerating price increases, and susceptible to regime changes in the form of crashes or volatile sideway plateaus, while the negative bubbles are associated with the downwardly accelerating price decreases, and are susceptible to regime changes in the form of rallies or volatile sideway plateaus.

Figure 2 shows the LPPLS confidence indicator for positive bubbles in red and negative bubble in green along with the index price in blue for the 10 major stock market indexes based on daily data from January 2, 2019 to May 31, 2020. Figure 2 (a) shows the detected SP500 bubble status. The positive confidence indicator on Feb 19, 2020, is up to 0.16, meaning that the 16% of fitting windows for this moment can successfully pass the filter conditions. It indicates that the detected LPPLS pattern is very reliable, and the positive bubble can be confirmed. It is highly possible that increasing trend of the price is not sustainable and the increasing rate of the price will be changed. The similar bubble patterns in Figure 2 (a) during the period of the 2020 stock market crash can also be found in other six subfigures in Figure 2, including: (b) DJIA, (c) NASDAQ, (e) DAX, (g) CSI300, (i) BSESN, and (j) BOVESPA, while the three remaining subfigures in Figure 2, including (d) FTSE, (f) NIKKEI and (h) HSI, only show a subtle cluster of positive bubbles during the period of the 2020 stock market crash.

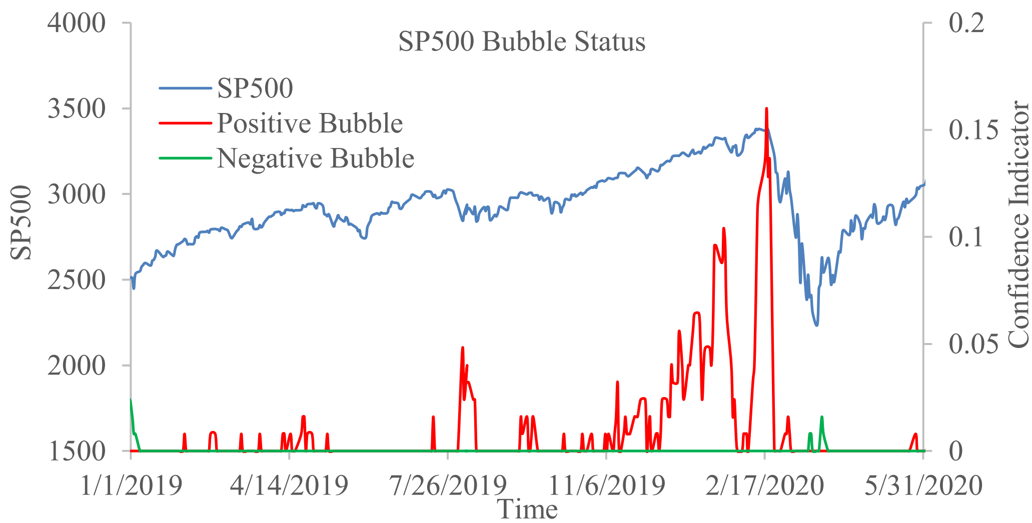
Table 1 summarizes the statistics of positive bubble detection results for the 10 stock market indexes based on daily data during the 2020 stock market crash from February to April 2020 and the related information of the peaks and valleys. During the 2020 stock market crash, 8 out of 10 indexes lost more than 30% of their values within five weeks. The BOVESPA index in Brazil stock market has the largest crash size of 45.4%, followed by the DAX index in Germany stock market with the crash size of 38.8%. To ensure the robustness of the crash type clarification, 5% confidence interval based on the empirical analysis is used to as the threshold to classify crash types for short-term analysis.

Table 1: Statistics of positive bubble detection based on daily data during the 2020 global stock market crash.

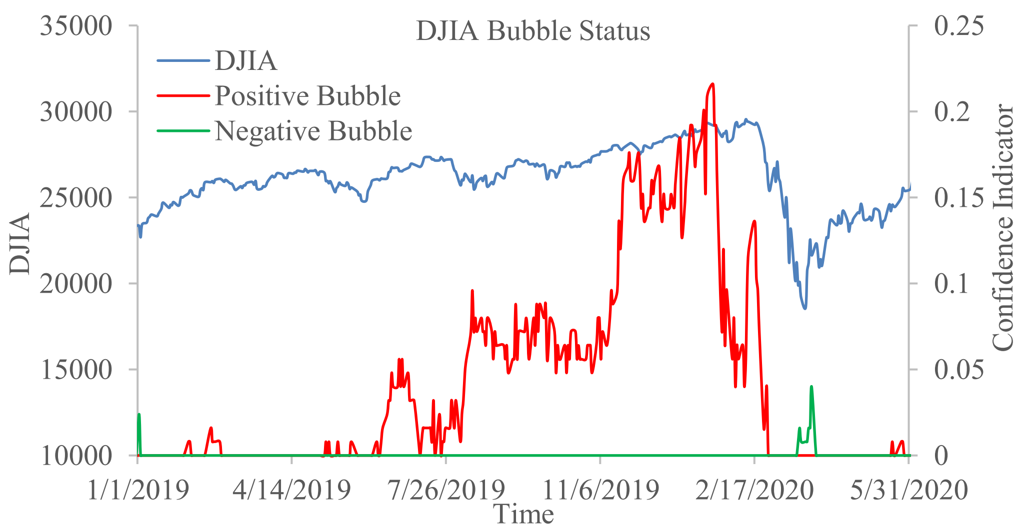
Index	Peak Date	Peak Price	Valley date	Valley Price	Crash Size	Peak CI	Type of Crash*
SP500	2/19/2020	3386.1	3/23/2020	2237.4	33.9%	16.0%	Endogenous
DJIA	2/12/2020	29551.4	3/23/2020	18591.9	37.1%	21.6%	Endogenous
NASDAQ	2/19/2020	9817.2	3/23/2020	6860.7	30.1%	12.0%	Endogenous
FTSE	2/19/2020	7457.0	3/23/2020	4993.9	33.0%	0.8%	Exogenous
DAX	2/19/2020	13789.0	3/18/2020	8441.7	38.8%	8.0%	Endogenous
NIKKEI	2/12/2020	23861.2	3/19/2020	16552.8	30.6%	0.8%	Exogenous
CSI300	3/5/2020	4206.7	3/23/2020	3530.3	16.1%	8.8%	Endogenous
HSI	2/19/2020	27655.8	3/23/2020	21696.1	21.5%	2.4%	Exogenous
BSESN	2/19/2020	41323.0	3/23/2020	25981.2	37.1%	6.4%	Endogenous
BOVESPA	2/19/2020	116518.0	3/23/2020	63570.0	45.4%	12.0%	Endogenous

*Note: To ensure the classification robustness, the 5% confidence indicator value is used here as the threshold.

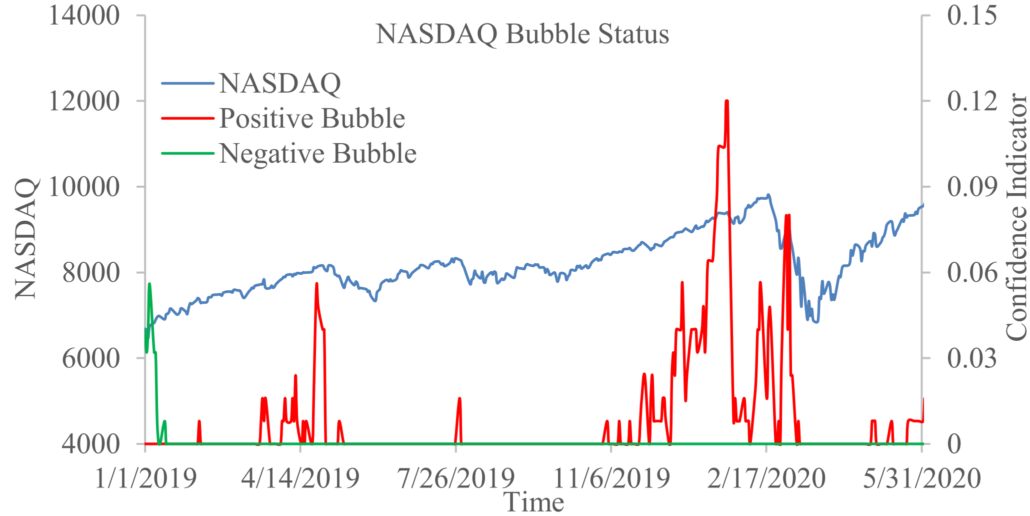
In Table 1, seven out of ten indexes, including SP500, DJIA, NASDAQ, DAX, CSI300, BSESN, and BOVESPA, have a peak confidence indicator value exceeding the 5% threshold, signifying that the price trajectories of these seven indexes clearly feature the signatures of the LPPLS model endogenous bubble state, and the subsequent crashes are endogenous stemming from the increasingly systemic instability of the stock markets. In contrast, the peak confidence indicator values for the remaining three indexes: FTSE, NIKKEI, and HSI, are smaller than the threshold value of 5%, indicating the absence of clear LPPLS bubble signatures in these price trajectories, and hence the subsequent crashes are exogenous stemming from the large external shocks, such as, the COVID-19 pandemic-induced market instability, the mass hysteria, the corporate debt bubble, etc.



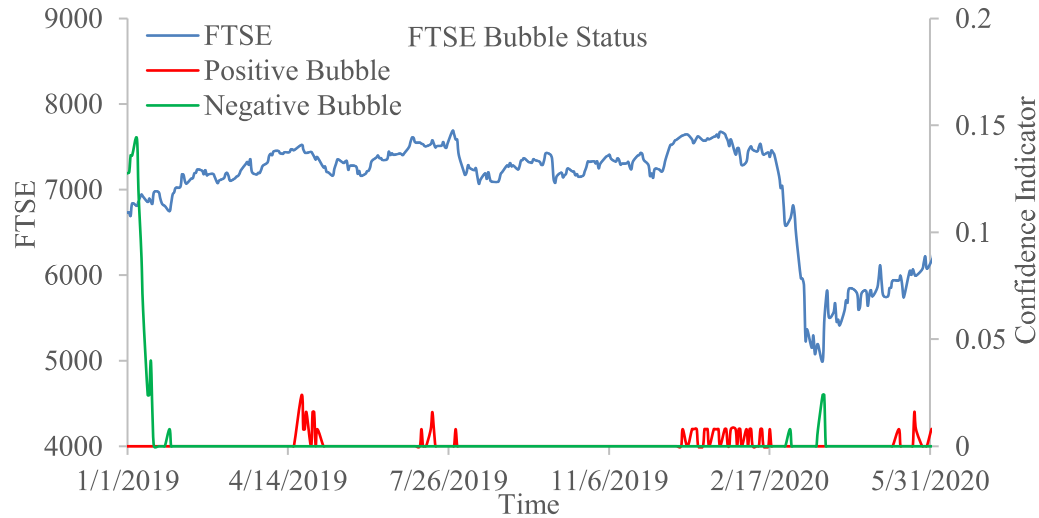
(a)



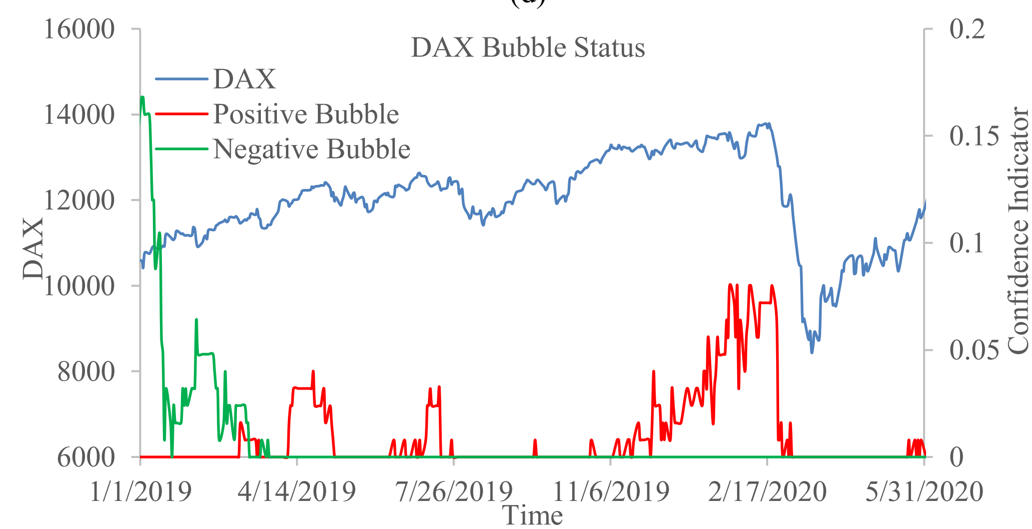
(b)


NASDAQ Bubble Status
NASDAQ
Positive Bubble
Negative Bubble
NASDAQ
Confidence Indicator
14000
12000
10000
8000
6000
4000
0.15
0.12
0.09
0.06
0.03
0
1/1/2019
4/14/2019
7/26/2019
11/6/2019
2/17/2020
5/31/2020
Time

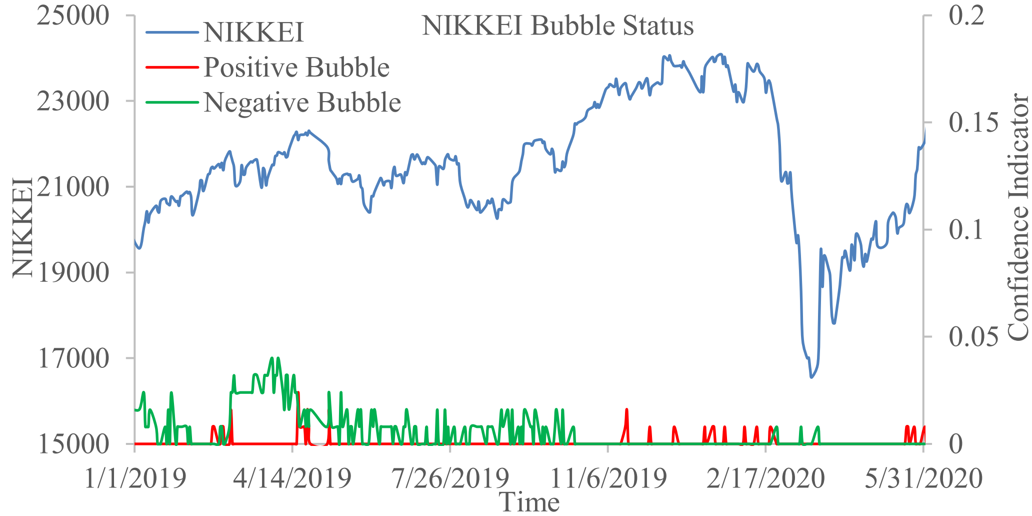
(c)


FTSE Bubble Status
FTSE
Positive Bubble
Negative Bubble
FTSE
Confidence Indicator
9000
8000
7000
6000
5000
4000
0.2
0.15
0.1
0.05
0
1/1/2019
4/14/2019
7/26/2019
11/6/2019
2/17/2020
5/31/2020
Time

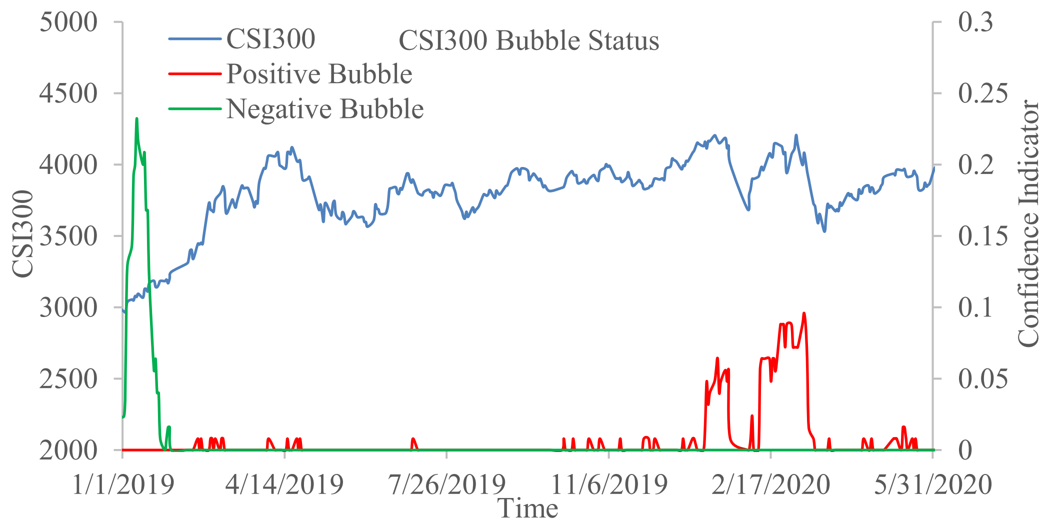
(d)


DAX Bubble Status
DAX
Positive Bubble
Negative Bubble
DAX
Confidence Indicator
16000
14000
12000
10000
8000
6000
0.2
0.15
0.1
0.05
0
1/1/2019
4/14/2019
7/26/2019
11/6/2019
2/17/2020
5/31/2020
Time

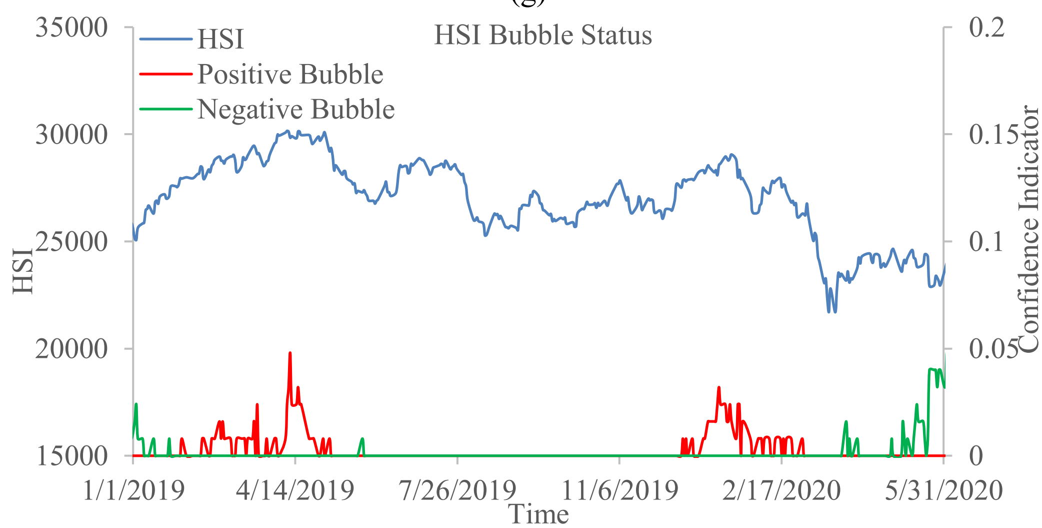
(e)


NIKKEI Bubble Status
NIKKEI
Positive Bubble
Negative Bubble
25000
23000
21000
19000
17000
15000
NIKKEI
0.2
0.15
0.1
0.05
0
Confidence Indicator
1/1/2019
4/14/2019
7/26/2019
11/6/2019
2/17/2020
5/31/2020
Time

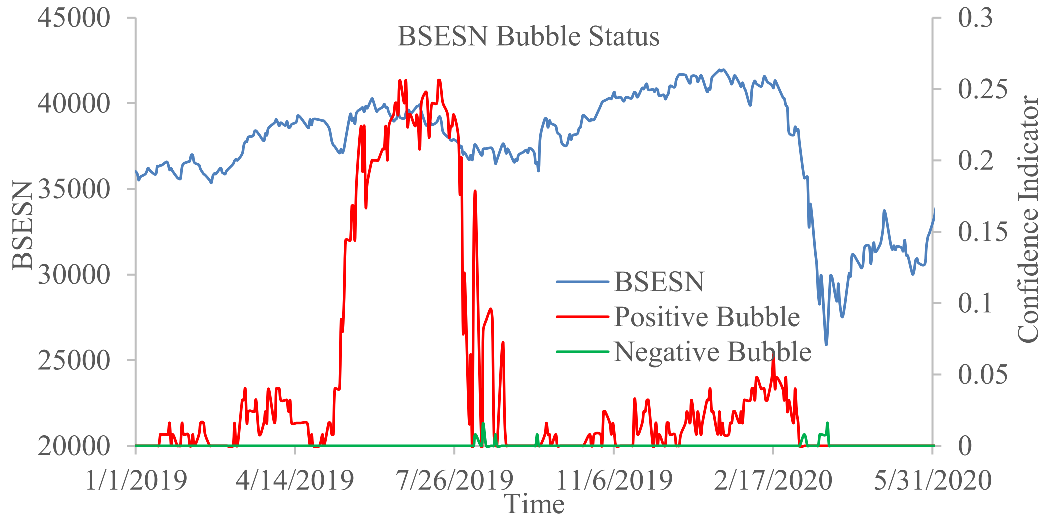
(f)


CSI300 Bubble Status
CSI300
Positive Bubble
Negative Bubble
5000
4500
4000
3500
3000
2500
2000
CSI300
0.3
0.25
0.2
0.15
0.1
0.05
0
Confidence Indicator
1/1/2019
4/14/2019
7/26/2019
11/6/2019
2/17/2020
5/31/2020
Time

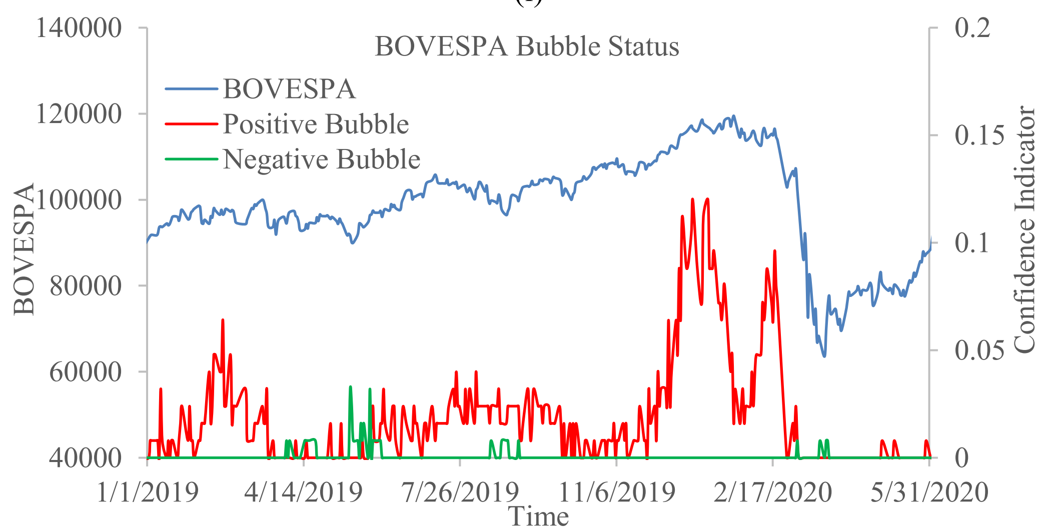
(g)


HSI Bubble Status
HSI
Positive Bubble
Negative Bubble
35000
30000
25000
20000
15000
HSI
0.2
0.15
0.1
0.05
0
Confidence Indicator
1/1/2019
4/14/2019
7/26/2019
11/6/2019
2/17/2020
5/31/2020
Time

(h)



(i)



(j)

Figure 2: LPPLS confidence indicator for positive bubbles is shown in red and negative bubbles in green (right scale) along with the index price in blue (left scale), for the 10 major stock market indexes based on daily data from January 2019 to May 2020.

4. Conclusions

In this study, we applied the LPPLS methodology to disclose the underlying mechanisms of the 2020 global stock market by analyzing the performances of the 10 major stock market indexes from both developed and emergent stock markets. We found that the LPPLS model can readily detect the bubble behavior of the faster-than-exponential increase corrected by the accelerating logarithm-periodic oscillations in the following seven indexes: SP500, DJIA, NASDAQ, DAX, CSI300, BSESN, and BOVESPA, indicating that the crashes for these seven indexes are endogenous due to the increasingly systemic instability of the financial markets. However, crashes in the remaining three indexes: FTSE, NIKKEI, and HSI, are exogenous caused by external shocks, such as the COVID-19 pandemic. Therefore, these are the only true COVID crash.

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