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Detection of Price Bubbles in Social Media Stock Markets

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ABSTRACT

Price bubbles are a common occurrence in the financial and asset markets. There exist numerous studies on detecting price bubbles considering different sectors of countries across the globe, however, very limited work is available on stock price bubbles related to social media. The present research takes a lead and detects multiple and periodically collapsing bubbles in stock prices of four popular social media platforms, namely, Facebook, Pinterest, Snapchat, and Twitter. The empirical analysis is based on the recently developed state of art generalized supremum augmented Dickey-Fully (GSADF) testing approach by Phillips et al. (2015) and it has the advantage of detecting multiple and periodically collapsing bubbles in contrast to rival approaches of bubble detection. The empirical results based on weekly and monthly closing prices spanning over the period 2012 to 2020, provide interesting insights regarding the existence and date stamping of periodically collapsing (multiple) bubbles. The empirical results may be helpful for social media developers and investors to forecast their future decisions.

1 Introduction

When there is a stock bubble, prices of stocks skyrocket to unusual numbers and then unexpectedly crash. There is no definite explanation of why they occur. Stock market bubbles as often as possible produce hot business sectors in initial public offerings (IPO markets), as brokers and customers spot chances in order to skim new stocks issued at swelled rates. These IPO markets misallocate stocks to regions directed by speculative trends, as opposed to undertakings creating longstanding financial worth. Normally when there is an excess of IPOs in the stock market, it creates a bubble, an enormous segment of the IPO companies' bomb totally and the bubble bursts, never accomplishing what was guaranteed to the speculators. Mississippi Scheme in France and the South Sea bubble in England were two famous early stock market bubbles. They collapsed in 1720, which resulted in bankrupting majority of the investors. Then in the twentieth century, there was a case of stock price bubbles in the American stocks right before the Wall Street Crash of 1929. It was then followed by another famous bubble, when in late 90s suddenly the NASDAQ Composite index inflated and then collapsed sharply due to the dot-com bubble. These bubbles occurred due to a number of technological innovations happening at this time period (the 1920s) as this was the golden era for technology as internet and e-commerce was introduced and was an emerging market. New companies got registered on the stock exchange and the demand for their stocks spiked as people were interested in these new markets. Other notable stock price bubbles are the Encilhamento, which led to a major financial crisis in Brazil in the late 1880s and the beginning of the 1890s. Then came the 'Nifty Nifty' of the 1970s in the New York stock exchange. According to economist these propelled the bull market. The most recent stock market bubbles are the 1987-89 Taiwanese stocks and the 1988-1991 Japanese asset bubble. Prices suddenly acerbated and economic activity increased tremendously. The money supply was left uncontrolled and the bubble finally burst in 1992, which left the Japanese economy, stagnated for a decade.

The primary objective of this research is to detect, and date stamp the existence of stock price bubbles in four big social media companies, namely, Facebook, Snapchat, Twitter and Pinterest. The first step is to detect whether any bubbles are present or not. If any bubbles are found then the next step is to identify the exact time period of their boom and bust. The maximum available data on closing prices is used for the chosen stocks of top four social media platforms and empirical analysis is carried out by recently proposed state of art approach by Philips et al. (2015) to detect and date stamp bubbles (if any exists) in the selected time series. Previous approaches have a drawback of detecting only single bubble, however, the GSADF approach has the advantage of detecting periodically collapsing multiple bubbles and thus is superior to any prior bubble detection methods used by most of exiting studies. The date stamping is a very useful indicator when studying bubbles as it helps identify the exact point when the bubble started and, also the date when it collapsed. This helps the investors in making smart financial decision. Further, it is important to study social media stock markets because of their importance, value and significance in today's world. Every other person has a free access to these platforms and is inclined towards these, due to their popular popularity. The numbers of users are not in Millions but in Billions and these platforms generate a lot of money due to advertisements and related features. The four platforms considered in this study are ranked at the top in terms of number of users and the monetary worth the stocks of these platforms have at the stock markets. Facebook remains at top with the most number of monthly users in 2020 worldwide (2.6 Billion users), Snapchat boosts 397 Million users per month that use this site to update and share their life with friends and the world, while the famous bookmarking site, Pinterest is at 367 Million monthly users and finally, Twitter at 326 Million users. It is reported that 40% of these users are active, daily for multiple times, making these platforms one of the most engaging sites on the internet. Initially, we had a plan to include three other famous social media platforms (LinkedIn, Reddit and YouTube) as well, but due to inaccessibility of data, we left it for some future research.

There have been several studies on bubble detection considering stocks indices (sectoral as well as at aggregate level) of different countries over different time periods, however, very few studies exist that analyse the case of bubble detection in social media platforms. To the best of our knowledge, Jarrow et al. (2011) is the only study that analyses the bubbles in the stocks of LinkedIn (a popular social media platform). The methodology employed by Jarrow et al. (2011) is different from the one being employed in our study and our study has the edge of utilizing a state of art approach (the GSADF approach by Philips et al. (2015)), that can detect periodically collapsing (multiple) bubbles and thus superior to any previous bubble detection approaches as existing approaches can detect only single bubble and thus existing methods may mislead when there are periodically collapsing multiple bubbles. This new approach is an updated version of the popular approach—the Supremum Augmented Dickey Fuller (SADF) test by Philips et al. (2011), designed to detect a single bubble. We couldn't consider LinkedIn in our research as the LinkedIn data is not freely available and due to funding constraints, we left it to be used in future research. The empirical results of this study yield interesting insights and suggest that only Facebook and Twitter witness bubbles while there is no evidence of bubble for the stocks related to Pinterest and Snapchat. Some relevant policy implications of the empirical findings are discussed at the end.

Rest of the paper is structured as:

The second section of this paper gives a brief introduction of the markets that have experienced price bubbles, followed by a review of literature covering key studies done on this issue and research gap. Section 3 briefly discusses the theoretical framework and the econometric methodology used, while

Section 4 provides empirical results and discussions. In the last section, we have given the conclusion and some policy recommendations.

2 Literature Review

The literature of detecting financial bubbles is vast. Its applications vary across different stock markets (at aggregate as well as sectoral level), industries, and commodities like bitcoin, gold, metals, oil, agriculture and food, real estate and oil, are few to mention. There are different variables for different sectors and commodities, that give rise to dramatic swing in prices causing bubbles. To detect and identify these bubbles, various researchers have used different techniques by considering data available at their time on the variables related to fulfil their specified objectives. It is important to note that the literature on bubble detection in social media platforms is very limited and to the best of our knowledge, only one study by Jarrow et al. (2015) is available considering the case of LinkedIn and analyzing bubbles in closing price series of LinkedIn stock by considering tick by tick data. So due to limited literature on the subject being considered in this research, we are providing very briefly the review of studies that have analysed bubbles in stock and commodity prices in other stocks (not necessarily social media stocks) for completeness.

Corbet et al. (2017) examine the presence and date stamping of bubbles in two famous crypto-currencies like Bitcoin and Ethereum using the methodology by Phillips et al. (2011) which examines fundamental drivers in bubbles present within these crypto-currencies. They put forward a recursive ex-ante method which is fit for identifying richness in asset price series during inflationary periods equipped for going about as an early notice framework. The fundamental drivers they tested as drivers of price increase were the blockchain position, liquidity as estimated by the volume of day-by-day exchanges and the hash rate. Having inferred proportions which are computationally and monetarily reasonable, the authors used these measures to distinguish and pinpoint the exact beginning and collapsing time of these bubbles. They have also examined the external effect that can exacerbate the existence of price bubbles in Bitcoin. One of these external events stated by the authors is time variation. In this paper they have stated Blau's (2017) argument that high volatility of Bitcoin is not identified with the rapid speculative movement in this time period. The vagueness in outcomes represents the discussions whether the cryptographic forms of money are a speculative investment asset or a currency. Due to this fact randomness tests are conducted and have found the returns to be significantly insufficient in the sample they used. In view of these results the authors have concluded that there is no clear evidence reason of a price bubble present in the market for both Bitcoin and Ethereum. The results of the three drivers (blockchain position, liquidity as estimated by the volume of day-by-day exchanges and the hash rate) show that in short-term they influence price dynamics of these crypto-currencies but then soon disappear.

Su et al. (2018) test for multiple bubbles in Bitcoin through the generalized sup Augmented Dickey-Fuller test put forward by Phillips et al. (2012, 2015). The results show that there have been four volatile bubbles in China and the U.S.A markets, fundamentally happening during the times of enormous floods in Bitcoin costs. An event bubble compares to the periods with a rise in price and then again, a fall in prices which causes bubbles to burst. This statement matches with the model by Gurkaynak (2008), in which asset price is broken down into fundamental and bubble parts. Specifically, exogenous shocks, including foreign or domestic financial and economic shocks lead to the start of price bubbles. In the end, the authors suggest that Bitcoin bubbles breakdown because of managerial intercession by financial authorities. Chaim and Laurini (2018) rely on nonparametric methods to empirically test the bubble existence in Bitcoin. Specifically, non-parametric estimator of Florens-Zmirou (1993) is used to assess the volatility for S&P500, EUR-USD, gold, and Oil and gauge the stochastic volatility model of Andersen and Piterbarg (2007), whose parameter space has a particular subset under which the Bitcoin's price is a strict local martingale. The results propose the presence of a bubble in Bitcoin costs from early 2013 to mid-2014, be that as it may, curiously, not in late 2017.

Jarrow et al. (2011) reveal that there are three types of asset price bubbles conceivable. Two out of these three types are found only in infinite horizon economies whereas the third type is found in finite horizon economies. The most relevant to actual market setting is of third type and to determine whether a bubble exists or not depends if the price process under a risk neutral measure is a martingale or a strict local martingale. If the result is a strict local martingale and the asset's price volatility is large enough, it is concluded that a bubble is present. The approach followed is based on a stochastic differential equation under the risk neutral measure driven by a Brownian motion. The empirical analysis is based on time series data taken from the alleged internet dotcom bubble of time-period 1998- 2001. The results for the three cases, reveals interesting insights, the first case confirms the presence of a bubble while the latter rejects it, whereas in the third case, the findings of the test are found to be inconclusive.

Harvey et al. (2013) use the recursive right tailed unit root tests to test for an explosive asset price bubbles by using recursive right-tailed Dickey-Fuller-type. The findings suggest that the right tailed test by Philips et al. (2015) finds multiple episodes of bubbles and especially this test perform well when there are bubbles in the middle part of the sample. The analysis done is based on the monthly data for the NASDAQ composite price index.

McDonald and Stokes (2013) analyze the monetary policy and housing bubble using Granger causality test and VAR model for the S&P/Case-Shiller 10-city monthly housing price index, federal funds rate and the 20-city monthly housing price index. The results of Granger causality for both the 10 city and 20 city S&P/Case-Shiller housing price indices predict that the interest rate policy of the Federal Reserve of pushed down the government funds rate and kept it falsely low and was a reason for the housing price bubble. The study concludes that the monetary policy contributed to both a housing rice bubble and a decline in housing prices. Chen (2012) on the other hand, conducts an empirical analysis of house price bubbles present in the Beijing housing market—the biggest commercial housing market in China. This analysis is done to determine if there is a bubble present for the selected time-period (1999-2009) and if so, how to deal with such a housing market price bubble. The analysis considers data on four variables namely, income, inflation, interest rate and construction cost and existence of bubbles is tested via vector error correction model. The results conclude that indeed a bubble exists in the Beijing housing market.

Jarrow et al. (2011) develop a model that can quantitatively determine whether the gold market is experiencing a price bubble. The focus is made on the difference between the market price and fundamental price. If any difference is found, then the gold price is experiencing a price bubble otherwise not. The empirical analysis is based on 'per second' data containing 73,695 observations obtained from Bloomberg and spanning the period Aug 25, 2011 till Sep 1, 2011. The study concludes that no bubbles are present in the gold market during the testing time-period.

Another method put forward by Bialkowski et al. (2011) to analyze the presence of a speculative bubble in the price of gold by making use of convenience yield model. The commodity dividends are used to derive gold's fundamental value. To observe the deviations of the real gold price from its fundamental worth, a Markov regime switching ADF test is used to recognize ex post and distinguish ex ante speculative gold price bubbles. This approach is therefore able to detect speculative bubbles in the gold market. The results obtained through this methodology show that no bubble is present.

Fantazzini (2016) studies the oil price crash of 2014/15 suggesting that there was a negative bubble present during this time period which diminished the oil prices past the level supported by economic fundamentals. Two methods are used to detect these bubbles existence, namely the SADF and the GSADF tests by Philips et al. (2015) and Philips and Shin (2014) and empirical findings supported bubble existence and their date stamping. Sornette et al. (2018) also analyze the bubbles in oil prices over the period 2006-2008 by using three methods, the simple LPPL model, the second order Weierstrass model and the second-order Landau model. The analysis is carried out via monthly data and the results obtained through this model suggest that the on-going oil price run-up has been enhanced by speculative behaviour of the type found during a bubble-like expansion.

Gerdesmeier et al. (2013) examine the existence of a bubble in the stock markets of OECD industrialized countries where they considered a sample of 17 OECD countries and also included the Euro area as well. The sample used for the analysis is quarterly data, spanning over the period 1969Q1 to 2008 Q3. The empirical analysis is based on panel unit root and cointegration tests, and the results suggest that the null of no bubble can be rejected country wise on the basis of the panel unit root tests while the same null could not be rejected when panel cointegration tests are used. Overall, the findings, however, do not provide a definite answer and thus further analysis is required.

Arshanapalli et al. (2016) test for bubbles in financial markets using West test which can detect bubbles but the thing it lacks is the identification of starting and ending dates of a bubble. The GSADF test by Philips et al. (2015) is also applied to show its superiority as it can be applied not only to detect multiple bubbles, but it also helps in date stamping the start and end point of a bubble. The findings of the study suggest that accessibility of real time monitoring instrument would altogether support financial specialists, retirees, and portfolio directors to rebalance their portfolios during such bubbles in the stock market.

Etienne et al. (2013) study the food markets for existence of bubbles over four decades by considering a sample of 12 agricultural commodities between time periods 1970-2011. The method used by them is a multiple bubble testing procedure of Phillips et al. (2012; 2015). This procedure is used to detect and date-stamp the exact bubble starting and bursting point. According to their results the entire sample has experienced a bubble.

Fatima and Ahmed (2019) test the existence of bubbles in agricultural commodities of Pakistan through the GSADF methodology by Phillips et al. (2015). Monthly data of seven major agricultural commodities is used over 18 years (2000-2018). According to results, there are bubbles present in all the seven commodities in Pakistan. Rice has the longest duration of bubble of 34 months (Jan 2006-Oct 2008).

Gäetan (2016) studies whether the Internet is facing another bubble keeping in mind the 1999-2000 Dotcom Bubble. He puts forward four criteria to determine whether there was a bubble present or not. First one is the determination of venture capital funding as this variable is the main culprit of a speculative bubble. Second is the initial public offerings. Third is to analyze the NASDAQ stock exchange as it played a major role in the Dotcom bubble phenomenon. It peaked high before crashing at the same speed when that bubble bust. Last criterion is to analyse different external signals. These external signals could be the real estate market or Venture Capital Confidence Index. Results of this study show that the venture capital funding is very high as its major portion is taken by the technology industry and then soon after this peak, a downward trend confirms that a bubble might be present. As for the IPOs, the data shows that majority of the companies went public before earning any profits, the same happened at the time of the Dotcom bubble which could signal that a new bubble might be on its way in the tech market. The insights regarding the NASDAQ stock exchange and the external signals are also provided, concluding that the venture capital confidence index has declined which may not confirm a bubble but if there is a bubble it confirms that it might burst very soon.

3 Theoretical Framework

In the commodities market, arrangement of bubbles predominantly is authorized to speculative demand and disarray in marketplaces. Concerning, different applicable psychological theories clarify this marvel, for example, Animal Spirit is a term by Jiménez & Vilella (2011) used in the greater fool theory and extrapolation theory. As per phycological theories, the markets behave unreasonably and cause assets/commodity price twisting and accordingly create unsteadiness in the market. The Keynesians idea of irrational conduct is backed by all these psychological theories (Caramugan and Bayacag, 2016). Rational commodity price theory by Pindyck (1993) by far the most employed theory in existing literature and is based on present value model which is applied on rational commodity prices (see Gali (2014) for details).

Let Pt be the cost or price of commodity considered by present and anticipated future instalments profit earned through the sale of the product and is signified as γ_{t+1}. The general arbitrage condition is:

$$P_t = F_t + B_t$$

Where, Ft and Bt respectively represent the fundamentals and the bubble component at time 't', and are given below:

$$F_t = E_t\left[\sum_{i=1}^{T-1} \frac{1}{(1+D)^i}\ (\gamma_{t+1})\right]$$

$$B_t = E_t\left[\frac{1}{(1+D)^{T-i}} P_t\right]$$

Where, D indicates the discount rate, Pt is the commodity price, and γ_{t+1} is the profit earned from sales of output or commodity. Note that, when there are no bubbles, i.e., B=0 then the price of an asset will get affect only by fundamentals.

4 Econometric Methodology and Data

4.1 Econometric Methodology

Methods used in current thesis depends on the work developed by Philips et al. (2011) and Philips et al. (2015) in order to detect multiple bubbles with beginning and ending time periods. Earlier, the standard right tailed Augmented Dickey Fuller (ADF) unit root test created by Dickey and Fuller (1979) is introduced for testing bubbles. However, a significant downside of this test is its inability to identify bubble's intermittent collapse. In order to solve this issue, Supremum Augmented Dickey Fuller (SADF) is introduced by Philips et al. (2011) for the detecting of single bubble which later extended by proposing a generalized version of it—the Generalized SADF (GSADF) by Philips et al. (2015) which one can use to reliably gauge the episodes in collapsing multiple bubbles. Thus, the GSADF can detect the multiple collapsing bubbles and hence provides a clear and deep picture of bubble existence. This study uses GSADF test. To set the stage, we use the same framework previously used by Hira and Ahmed (2019) and Ahmed et al. (2021), and thus, we consider the following linear regression model:

$$X_t = \rho + \omega X_{t-1} + \sum_{k=1}^{n} \theta_k \Delta X_{t-k} + \epsilon_t \qquad \text{eq. [1]}$$

Where X_t represents the closing prices, ρ represents intercept, the coefficient of first lag of X_t is ω, and coefficient of ΔX_{t-k} is θ_k, and ϵ_t is an error term at time $'t'$ with zero mean and variance being a positive constant.

The focus of this research is to detect explosive behaviour (bubbles) of price series. For this reason, the following null hypothesis is generated:

H_0: $\omega = 1$, against the right tailed alternative: H_1: $\omega > 1$

Few notations are being introduced to facilitate the analytical expressions discussed below. First, we have normalized the sample containing 1 to T observations into a unit interval [0, 1]. Let ADF_{s_1,s_2} and $\omega_{s1,s2}$ respectively show the ADF-statistic and the estimated coefficient of X_{t-1} in eq. [1] over the sample [S_1, S_2]. Additionally, let Ws be the window size represented by $Ws = S_2 - S_1$.

The GSADF test recommended by Phillips et al. (2015) is the commonly utilized because of its flexible and adaptable window size used in estimation. The starting point of sample, i.e., s_1, is allowed to vary over the interval [0, s_2-s_0]. The ADF_{s_1,s_2} statistic is calculated for each estimation window and the GSADF is calculated via the following relation:

$$GSADF(s_0) = \underbrace{sup}_{\substack{s_2 \in [s_0,1] \\ s_1 \in [0, s_2 - s_0]}} \{ADF_{s_1,s_2}\}$$

The date stamping of bubbles is done as: The point where the value of backward sup ADF ($BSADF_{s2}$) statistic crosses the corresponding critical value from below is the start date of bubble (say Ts_e), and the point where the value of backward sup ADF ($BSADF_{s2}$) statistic crosses the corresponding critical value from above is the end date of bubble (say Ts_f). This results in the following estimates of bubbles:

$$\hat{s}_e = \underbrace{sup}_{s_2 \in [s_0,1]} \{s_2 : BSADF_{s_2}(s_0) > \delta_{s_2}^{\beta_{T_{s_2}}}\}$$

$$\hat{s}_f = \underbrace{sup}_{s_2 \in [\hat{s}_e,1]} \{s_2 : BSADF_{s_2}(s_0) < \delta_{s_2}^{\beta_{T_{s_2}}}\}$$

Where, $\delta_{s_2}^{\beta_{T_{s_2}}}$, is $100(1-\beta_T)\%$ critical value of Sup ADF statistic for T_{s_2} observation, while, $BSADF_{s_2}(s_0)$, $s_2 \in [s_0, 1]$ is the backward SADF statistics which is related to GSADF via the relation:

$$GSADF(s_0) = \underbrace{sup}_{s_2 \in [s_0,1]} \{BSADF_{s_2}(s_0)\}$$

The sup ADF (SADF) is given by:

$$SADF(s_0) = \underbrace{sup}_{s_2 \in [s_0,1]} \{ADF_{s_2}(s_0)\}$$

Where, $ADF_{s_2}(s_0)$ is the standard right tailed ADF statistic.

4.2 *Source(s) of Data*

All the data used in this research is extracted from Yahoo Finance. The focus is made on top four social media platforms including Facebook, Pinterest, Snapchat and Twitter. To include maximum available data, the chosen time-period is different for all four social media platforms. The data frequency is monthly for three out of four social media platforms (Facebook, Snapchat and Twitter) while due to very low number of monthly observations for Pinterest, we took weekly data for it. The key variable we have chosen to detect stock price bubble is the closing price as it is standard benchmark usually used to keep track of performance of a stock overtime. It is important to note that there is no need to take same time span for the chosen stocks as the methodology is based on GSADF test which analyses each series separately and detects bubbles, thus, it is wise to take longer time series covering maximum available data and the same is considered by us while taking a decision, regarding choice of data span. Table 1 gives details of time span and number of observations considered for each of four social media platforms.

Table 1

Details of Data Series

S. No.	Social Media Platform	Frequency	Data Span	Observations
1	**Facebook**	Monthly	May 2012 to Mar 2020	95
2	**Pinterest**	Weekly	3rd Week of Apr 2019 to 2nd Week of Mar 2020	48

3	**Snapchat**	Monthly	Apr 2017 to Mar 2020	36
4	**Twitter**	Monthly	Nov 2013 to Mar 2020	77

Figure 1 shows the plots of closing prices of each of top four social media stock series including Facebook, Twitter, Snapchat, and Pinterest. Due to low number of monthly observations for Pinterest, we have used weekly data for it while for the rest of three social media, monthly data is used. From the graphs, a clear upward trend can be seen for closing prices of Facebook while the other three series show fluctuations. Twitter starts off with a high trend in 2014 and then there is a drop which lasts till 2017 and then an upward trend is seen from 2018 and then there is a slight fall from 2019 onward. Snapchat also starts at a high and then has a fluctuating trend while Pinterest shows downward trend overall for the selected time- period.

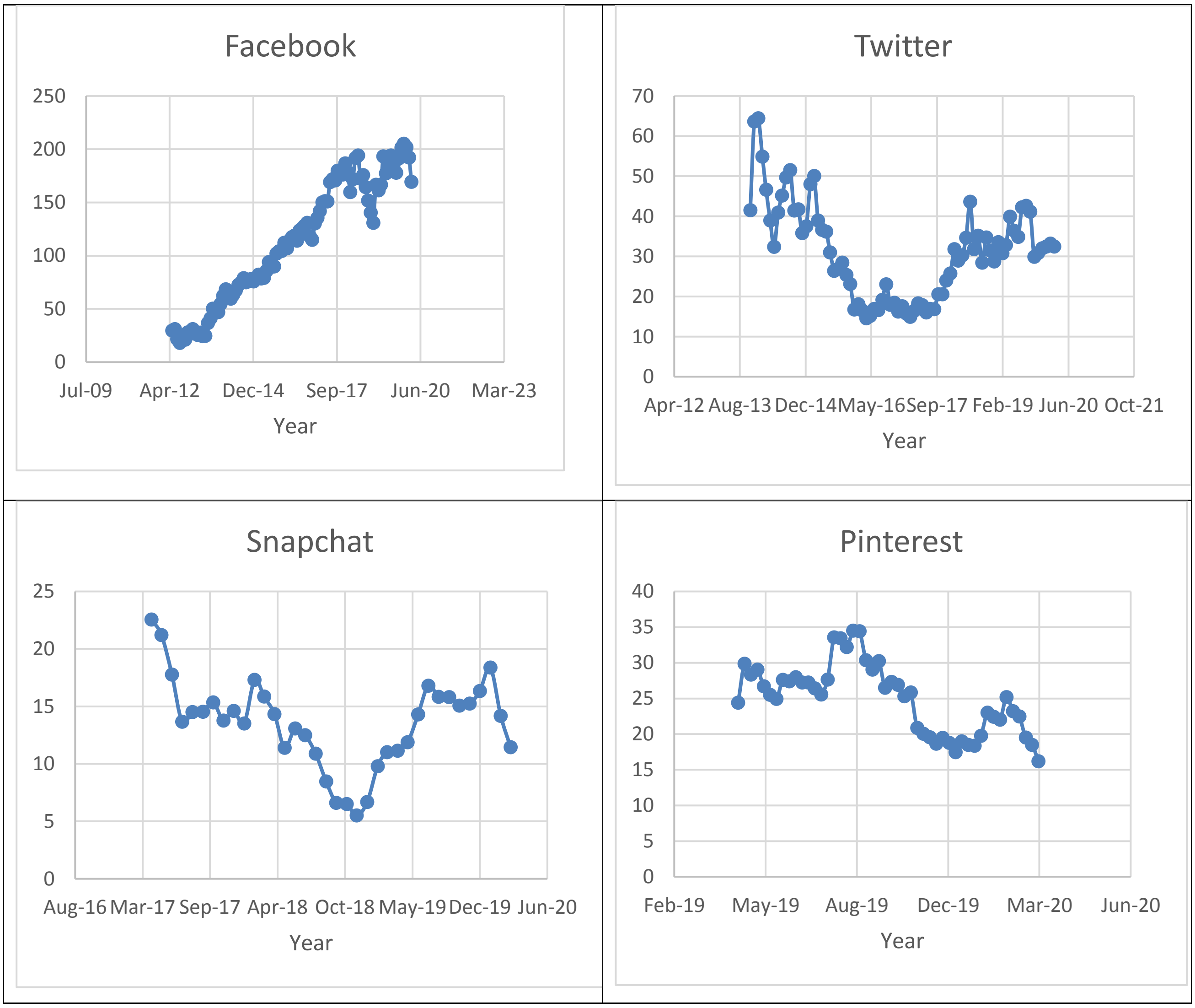

Figure
Plot of Closing Prices of top Four Social Media

5 Empirical Results and Discussions

We start the empirical analysis with summary statistics given in Table 2 below for closing prices of all four social media companies (Facebook, Pinterest, Snapchat and Twitter).

Table 2

Summary Statistics of Closing Prices of Social Media Companies

Social Media	Frequency	Mean	SD	Median	IQR	Min	Max	Skew	Kurt
Facebook	Monthly	112.36	58.02	114.28	106.20	18.06	205.25	-0.07	1.68
Pinterest	Weekly	24.97	4.89	25.53	7.89	16.21	34.50	0.10	2.14
Snapchat	Monthly	13.55	3.87	14.24	4.55	5.51	22.55	-0.13	3.09
Twitter	Monthly	31.11	11.79	31.45	19.75	14.62	64.50	0.55	2.97

Note: Total number of observations in Facebook, Pinterest, Snapchat and Twitter are 95, 48, 36 and 77 respectively.

From Table 2, it can be noted that Facebook has the highest priced closing stock at 205.25USD, whereas, Snapchat has the lowest priced closing stock price at 5.51USD. The average and median prices of Facebook are much higher than the other three social media platforms which makes it the most valuable and expensive platform at the stock market compared to other three, while Snapchat, on the other hand, has a lowest average as well as median closing price among the four considered social media platforms. The closing price series for Facebook and Snapchat are negatively skewed while the other two series are positively skewed. The value of kurtosis for Facebook and Pinterest is significantly lower than 3—the benchmark value for the normal, so we can say that the distributional shape of these series is platykurtic while for the Twitter and Snapchat series, it is mesokurtic.

Our findings for closing stock prices of all four selected social media platforms (Facebook, Snapchat, Twitter, and Pinterest) through GSADF test are provided in Table 3. The null hypothesis of no bubble is tested against the alternative of existence of bubble in considered series. The critical as well as p-values of GSADF statistic are calculated via Monte Carlo simulations with 1,000 replications and with zero lag order chosen via Akaike-Information Criterion (AIC). The null hypothesis is tested at 90%, 95% and 99% significance levels in contrast to the conventional methods where significance level is taken at 1%, 5% and 10% as GSADF is a right tail test.

Table 3

Results of GSADF Tests for Top Four Social-Media

Facebook	**Time Span** May 2012 to Mar 2020	**GSADF Statistic** 2.638** (0.015)
Critical value		
99%	2.757	
95%	2.112	
90%	1.744	
Snapchat	**Time Span** Apr 2017 to Mar 2020	**GSADF Statistic** 0.534 (0.470)
Critical value		
99%	2.620	
95%	1.816	
90%	1.497	
Twitter	**Time Span** Nov 2013 to Mar 2020	**GSADF Statistic** 2.173**

		(0.033)
Critical value		
99%	2.604	
95%	2.003	
90%	1.617	
	Time Span	**GSADF Statistic**
Pinterest	3rd Week of Apr 2019 to 2nd Week of Mar 2020	0.024 (0.772)
Critical value		**GSADF**
99%	2.795	
95%	1.894	
90%	1.524	

Note: The p-values are provided in parentheses and ** denotes significance at 95% significance level.

It can be seen from the p-value corresponding to GSADF-statistic in Table 3 that null hypothesis of no bubble gets rejected for two out of four social media platforms, namely, Facebook and Twitter while for the rest of two (Snapchat and Pinterest), it is not rejected, implying that there is evidence of existence of bubbles in Facebook and Twitter while there is no evidence of existence of bubbles in Pinterest and Snapchat.

Table 4 shows the details of date stamping of bubbles. Specially, the details are provided on start and end dates of bubble(s) (if any) as well as the total duration of bubble period is provided which can help in distinguishing short-term bubbles from the long-term bubbles. Bubbles emerged only in two out of four social media platforms, i.e., Facebook and Twitter while no bubble is observed for the rest of two social media platforms (Snapchat and Pinterest).

Table 4

Bubble Date Stamping of Top Four Social Media Platforms

Facebook			
S. No.	**Bubble Start Date**	**Bubble End Date**	**Duration in months**
1	Dec 2013	Feb 2014	3
2	Aug 2014	Sep 2014	2
3*	Jan 2016	Jan 2016	1
4*	Apr 2017	Apr 2017	1
5	July 2017	Jan 2018	7
Twitter			
S. No.	Bubble Start Date	Bubble End Date	Duration in months
1*	Feb 2018	Feb 2018	1
2	May 2018	June 2018	2
Snapchat			
No Bubbles were found			

Pinterest	
No Bubbles were found	

*Bubbles with one month duration is excluded as per guidelines in Philips et al. (2015)

From Table 4, we can clearly see that there exist three bubbles in Facebook while only one bubble occurs in Twitter. Note that as per Philips et al. (2015), we cannot consider periods where the duration of bubble is of one month duration only. However, for completeness and to keep record of such dates, we have retained these periods in Table 4 as well. Note that, for Facebook, the only major and longest bubble is of seven months duration which occurred during July 2017 till Jan 2018, while the second bubble is of three months duration (Dec 2013 to Feb 2014) while third one is of two months duration. In case of Twitter, only one bubble is seen which occurred during the period May 2018 till June 1018. Note that no bubble is seen in the closing prices of Snapchat and Pinterest.

The details of start of collapsing dates of bubbles for the Facebook and Twitter are provided in Figure 2 and 3. The point where the backward SADF statistic crosses the critical value from below is the bubble start date while where the same crosses from above is the bubble collapsing date. The plots of original series are also provided in both figures for comparison with the value of test statistic.

Note that our results are not directly comparable with any of existing studies as no prior research is available on the issue of bubbles in social media stocks. The only study that closely relates to our research is by Jarrow et al. (2015) which analyze the bubbles in LinkedIn by considering minute by minute data and showed that there exist bubbles in LinkedIn stocks. Unfortunately, the minute-by-minute data is not freely available so we couldn't get the same data and thus, we considered data which is publicly available and thus, our focus in this study is only on top four social media platforms and not the LinkedIn. However, future research can be conducted to provide a comparison of all popular social media platforms by including LinkedIn, Reddit and YouTube as well.

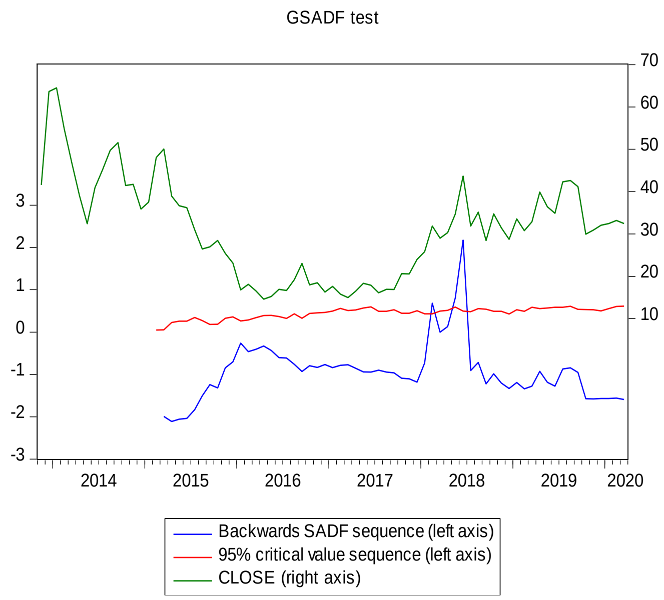

Figure 2
Date Stamping of Bubbles for Facebook

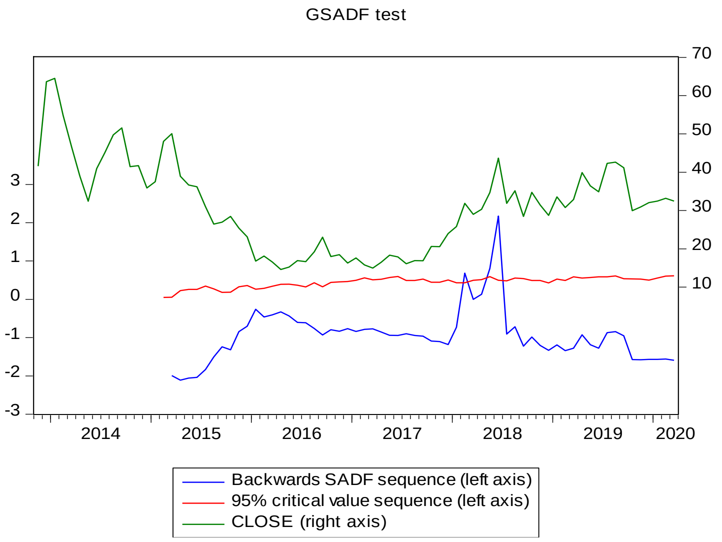

Figure 3
Date Stamping of Bubbles for Twitter

6 Conclusions and Policy Recommendations

Price bubbles are a common occurrence in the financial and asset markets representing a sudden acceleration in prices followed by a sudden collapse, thus bursting the bubble. It all started from the 'Tulip Mania' in Netherlands. Then economists started studying why these bubbles form and what causes them to burst. There are different causes for different types of bubbles. There are numerous studies on price bubbles is different sectors but there is currently only one available on stock price bubbles related to social media stocks by Jarrow et al. (2011) considering the stocks related to LinkedIn. As social media has a huge impact and is a major source of information in today's world, so, it will be fruitful to analyze the stocks of social media platforms for bubbles existence. The chosen platforms are of have high monetary worth and billions of active users. This makes them a great subject to test. In addition, very limited literature on this issue sparked our interest and we initiated this study considering top four social media stocks, namely, Facebook, Twitter, Snapchat and Pinterest. The empirical analysis is based on maximum available time series data and detection of bubbles is done by recently proposed state of art approach by Phillips et al. (2015). The findings provide evidence of existence of bubbles in two out of four social media platforms considered namely Facebook and Twitter, however, no bubble is witnessed in the closing prices of Pinterest and Snapchat.

It is known that a persistent increase in price instability and fluctuations can have profound social and monetary impacts. These empirical results can be utilized with other data; for example, major components which can cause the bubbles to form, and this could assist in foreseeing any future bubbles that may occur in the other financial and asset markets. This can help in the prevention by taking the necessary steps.

It is likewise extremely fundamental to relieve weight on prices by upgrading and enhancing productivity development and investment in these markets and sectors that has indicated a propensity to form a bubble. Cautious contemplations ought to be given to the major macroeconomic factors like stock and inventory maintenance, maintaining demand and supply and keep balance to sustain equilibrium, exchange rate movements as well as speculative drivers that add to the chance of bubble formation.

As our study is unique in nature and not a lot has been done on this subject, it is a great work for social media developers and investors to forecast their future decisions based on these findings. The research can be extended by considering high frequency data and also including stocks of other social media platforms such as YouTube, LinkedIn and Reddit and most importantly knowing the exact reasons of bubble emergence and collapse.

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