Search Volume based Attention Data Provides Insights into the Feedback Mechanisms in Financial Market Bubble Periods

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ABSTRACT

Studies of public attention in the feedback mechanism in market bubbles has been limited due to the unavailability of data sources. Meanwhile, recent studies of public attention data based on the Internet search volume index (SVI) have failed to consider the feedback mechanism in market bubbles. This paper is to utilize the SVI as the novel and leading measurement of public attention to study the stock market bubble generating feedback hypothesis. We select and compare two groups of SVIs and corresponding stock composite indices. The first group stock composite indices feature with significantly large market bubbles while the second group's indices are not. Several significant findings include, first, strong evidence of positive and negative feedback between the SVI based public attention and stock index is detected throughout the market bubble process; second, the same feedback mechanisms are rare in non-bubble periods, where the unidirectional transfer function model works well; third, the correlation between the SVI and stock index is much higher in the bubble periods than that in non-bubble periods, and the SVI is typically stationary in non-bubble periods but becomes non-stationary in bubble periods. Last, the bi-variate relationship of feedback is discussed and analysis is provided for its macro-level behaviors.

Introduction

Financial market bubbles can come with catastrophic influences on the whole economy, and therefore understanding how they are generated is important for the macro-level risk management. One bubble generating mechanism hypothesis is the feedback between investors confidence and the market prices. In this case, the surging stock prices can raise investors confidence and higher confidence will lead to higher demands of shares, resulting even higher stock prices. As the positive feedback continues, market bubbles are generated. On the other hand, the demand of shares cannot expand infinitely. Bubble can crash in a similar way, which involves a negative feedback loop[1]. This feedback hypothesis is intuitive and easy to understand, but it remains untested because of the difficulty to quantify and measure investors confidence, which is subjective and usually ambiguously defined.

However, the public attention can work as a substitute for investors confidence. As indicated by Robert Shiller, when speculative price goes up, creating successes for some investors, this may attract public attention, promote word-of-mouth enthusiasm(the negative feedback in the same feedback mechanism is called word-of-mouth pessimism by Shiller[2]), and heighten expectation for future price increases; this process in turn increases investor demand and thus generates another round of price increases[2]. In contrast to the investors confidence, the public attention is highly objective and easy to quantify. Studying the bi-variate relationships between the SVI based public attention and stock prices at the presence of market bubbles will provide more insights for understanding the bubble generating mechanism.

Similar to the investors confidence, the public attention connects with our psychological behaviors and it has been well studied both theoretically and empirically because of its cognitive significance in information gathering for decision making and the availability of its objective proxy measures in financial markets such as the number of news releases, extreme returns, newly opened market accounts[3−8] Most previous studies are only able to extract evidence of high correlations between market prices and attention indices. For example, Robert Shiller has utilized the number of media reports and the number of investors clubs, and found the high correlation between the attention proxies and the stock prices during the market bubble period[1]. However, these proxies have limited consecutiveness compared with stock prices, therefore the relevant in-depth time series studies are still limited. As mentioned by Shiller[2], In fact, academic research has until recently hardly addressed the feedback model, previous studies addressing the feedback models could not dig deep without qualified public attention data, and findings there-from are mainly experimental and empirical evidence[9–13]

Fortunately, the development of the Internet technology gives rise to the web search volume index (SVI). The SVI, representing the quantity of web queries by certain key words in search engines, can reflect the level of public attention. As a novel measurement of public attention, the SVIs have been fruitfully studied in various academic establishments[14–25] In financial studies, the SVI proved its leading role among other measures of public attention, which likely stemmed from their close link to decision making process. Compared with other measurement, an outstanding merit of SVIs is their availability and abundance, which make them suitable for in-depth analysis. For example, Bordino et al. have provided evidence that SVIs can predict trading volumes[14] Da et al have comprehensively studied SVIs in the financial context and found evidence that SVIs leads other financial attention measurement. Moreover, evidence show that SVIs most likely represent the attention of unsophisticated individual investors[21], who are main source of noise traders and are more amenable to the herding behavior that cause market bubbles.These features of the SVI make it a perfect candidate for the public attention measure in financial studies. However, most of these studies only focused on the correlation analysis and the predictability of SVIs for stock markets, but ignored the potentials of SVIs as the measure of public attention in the study of the feedback mechanism hypothesis where market bubbles are generated. Therefore, we will specifically address the bi-variate relationship between the SVIs and stock prices over the market bubble periods and try to find the evidence of the feedback mechanisms. Next, we will introduce our data. Then we will present our methods used in this paper and give the results of the statistical tests. Finally we will discuss the results obtained and conclude this paper.

Data

As the study focuses on the correlation between the SVIs and the stock prices during bubble periods, the availability of SVIs and the existence of bubbles are the two constrains in our data selection. In consideration of the first constraint, the availability of SVIs, Google Trend and Baidu Index both jump in our view because they both provide sufficient SVIs and respectively they represent the top two largest economies globally. In terms of the second constraint, the existence of market bubbles, Baidu Index is a more suitable choice versus Google Trend as bubble test indicates insignificant bubbles for Google Trend. Therefore Baidu Index is selected as the major data source for our study of feedback mechanism during bubble periods, whereas Google Trend is used to provide contrast during non-bubble periods.

- Baidu Index(Group 1):China Shanghai Security Composite Index Index, China Shenzhen Security Component Index (SZC),China Growth Enterprises Board Index (GEM) with theirs Baidu Index SVIs respectively. Data in this group are drawn on a daily basis from the Chinese market between 4 Jan.,2012 and 29 Jan.,2016. They contain the most recent market bubble started in 2014. Baidu Index is used as the source for SVIs as it has better geographic fit for Chinese investors and provides higher data frequency than Google Trend. The key words for obtaining the SVIs are respectively the name of each stock market index in Chinese.
- Google Trend(Group 2): Nasdaq Composite(NAS), Dow Jones Industrial Average(DOW),S&P 500 Index(SP500) with theirs Google Trend Index SVIs respectively. Data in this group are drawn on a daily basis from the American stock market between 3 Jan., 2012 and 29 Jan.,2016. Since the Google trend puts constraints on the maximal number of the available data on a daily basis, we have to re-scale the data based on the weekly data[26]. The key words for obtaining the SVIs are respectively the name of each stock market index.The key words for obtaining the SVIs are respectively the name of each stock market index in English.

Unlike most studies using single stocks, we choose composite index in order to avoid ambiguities in keywords selection (e.g., using the name of the listed company may not imply stock-related information demand) and to avoid potential information loss when using averaged SVIs from different key words. Though conservative, it is effective given the high correlation between the one-key-word index and the general attention of the whole market.

Our data are plotted in Figure 1. The graphs depict the standardized stock indices and their SVIs. The data present common features in all markets. One example is that the SVIs remain relatively stable when the stock markets are stable whereas high serial correlations are more frequently identified when stock markets are surging. Through market bubble test and separation of bubble and non-bubble periods, we found that the correlation between the two series is much higher in the bubble periods than in the non-bubble periods. (See the section, *Stationarity Test of SVIs*, in supplementary files for details.)

Methods

In this paper, we first try to detect the bubble(bubble strength) and then verify the feedback(feedback strength) during the bubble period. In order to present visually informative results, we will use indices in which the strength of the bubble and the

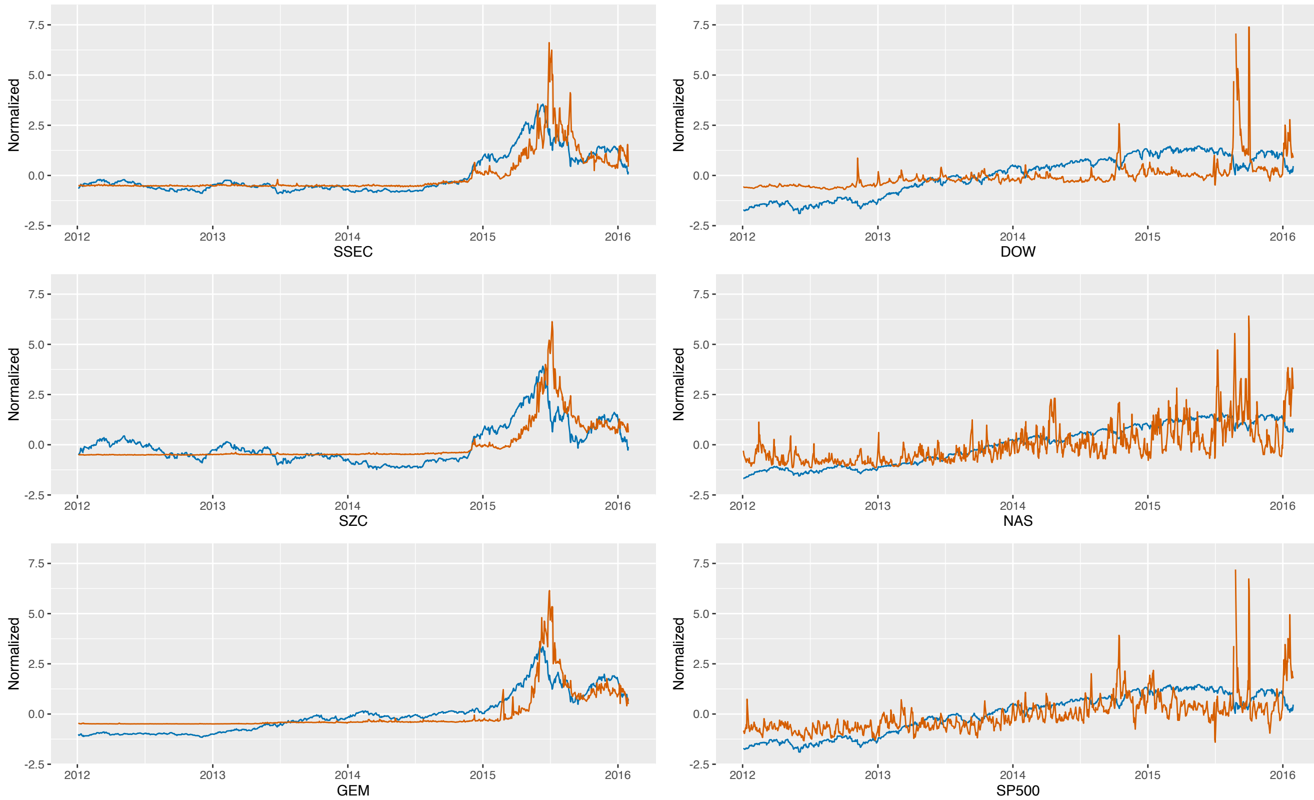


Figure 1. Stock Market Indices(blue) and Search Volume Indices (orange). The left three plots are Group 1; the right three plots are Group 2

strength of the feedback can be measured over a time period. So we will choose two temporal measurements(D.F. statistic & F-value) for bubble strength and feedback strength respectively. In the following equations, S_t and P_t represent stock prices and SVIs respectively.

The Bubble Dectection: Rolling ADF Test

For the bubble strength, we choose the right-tailed rolling ADF test and take the ADF statistics as the measure. The first right-tailed ADF test, which was proposed by Diba and Grossman[27], Evans then found that the sample span was too large to detect the bubble[28]. Later, Philips et al. proposed the recursive right-tailed ADF test[29], one of which is the rolling right-tailed ADF test that can measure the bubble evenly across the sample span. The right-tailed ADF test model is specified as

$$\Delta log(S_t) = \beta_0 + \delta S_{t-1} + \sum_{i=1}^{p_s} \beta_i \Delta log(S_{t-i}) + \varepsilon_{s,t} \tag{1}$$

where Δ is First order difference operator, p_s is the lag order, and $\varepsilon_{s,t}$ is the white noise.(See the section,*The Detecting and Determination of Bubble Test*, in supplementary files for details.) The rolling test in time series divides the whole sample with N observations into N-n+k sub-samples and each subsample has n observations, where k is the step size. In each subsample, Equation 1 is estimated and one ADF statistic is obtained. So we will have N-n+k statistics. In this test, we choose k=1, and the lag order is fixed as 1 throughout this paper. The bubble strength measurement is the ADF statistic from each sub-sample, and the time assigned to each ADF statistic is the last date of the corresponding sub-sample.

A critical parameter in the rolling ADF test is the window size n, which directly measures the size of the bubble that we want to detect. Two criteria are met when choosing the window size, namely a window size that corresponds to meaningful time span (i.e., a month or a year) and neatly captures the market bubble. Here we have selected three window sizes and carried out the rolling ADF test respectively on each of them. For our data, by comparing the results of sizes 60, 120 and 240 (approximately a quarter, a half-year and a year on a trading-day basis), size 240 is a better choice than the other two given its ability to detect the single macro-bubble in the market.

The Feedback Verification: Rolling Granger Causality Test

For the feedback strength, we use the bidirectional Granger Causality Test, the most popular test for bi-variate causal relationships that has been utilized in various subjects to test feedback loops[30–35]. In this case, the positive feedback specifies that the increase in stock prices will Granger cause the increase of SVIs, and vice versa. However, both the negative and positive changes in St will typically correspond to a positive response of ΔP_t.(This relation is empirically reasonable, and is confirmed in the transfer function models established in the non-bubble periods. See the section,*Transfer Function Models for the Non-Bubble Periods*, in supplementary files for details.) Therefore, we need to exclude the positive response of ΔP_t caused by negative ΔS_t. In establishing the positive feedback test, our modification uses sign operation method (see equations below), along with other sign separation methods and studies of asymmetric properties in financial time series analysis[36–43]

$$\Delta S_t^p = \begin{cases} \Delta S_t, \Delta S_t > 0 \\ 0, \Delta S_t \le 0 \end{cases} \quad \Delta P_t^p = \begin{cases} \Delta P_t, \Delta P_t > 0 \\ 0, \Delta P_t \le 0 \end{cases} \tag{2}$$

The Granger Causality Test for positive feedback will be:

$$\Delta S_t^p = \alpha_s \sum_{i=1}^{p} \beta_{si} \Delta S_t^p + \sum_{j=1}^{p} \delta_{sj} \Delta P_t^p + \varepsilon_t \tag{3}$$

$$\Delta P_t^p = \alpha_p \sum_{i=1}^{p} \beta_{pi} \Delta S_t^p + \sum_{j=1}^{p} \delta_{pj} \Delta P_t^p + \varepsilon_t \tag{4}$$

On the other hand, with similar separation method, we can test whether there is feedback between the negative change in stock prices and the positive change in search volume. Unlike the positive feedback hypothesis, the increased attention here could represent the loss of confidence and the spread of concerns in the stock market, and this relation can be explained as negative feedback, whose properties are opposite to its positive effect and could cause the bubble to halt and even crash. Thus similarly, we have:

$$\Delta S_t^n = \begin{cases} \Delta S_t, \Delta S_t < 0 \\ 0, \Delta S_t \ge 0 \end{cases} \quad \Delta P_t^n = \begin{cases} \Delta P_t, \Delta P_t < 0 \\ 0, \Delta P_t \ge 0 \end{cases} \tag{5}$$

$$\Delta S_t^n = \alpha_s \textstyle\sum_{i=1}^{p} \beta_{si} \Delta S_t^n + \sum_{j=1}^{n} \delta_{sj} \Delta P_t^p + \varepsilon_t \tag{6}$$

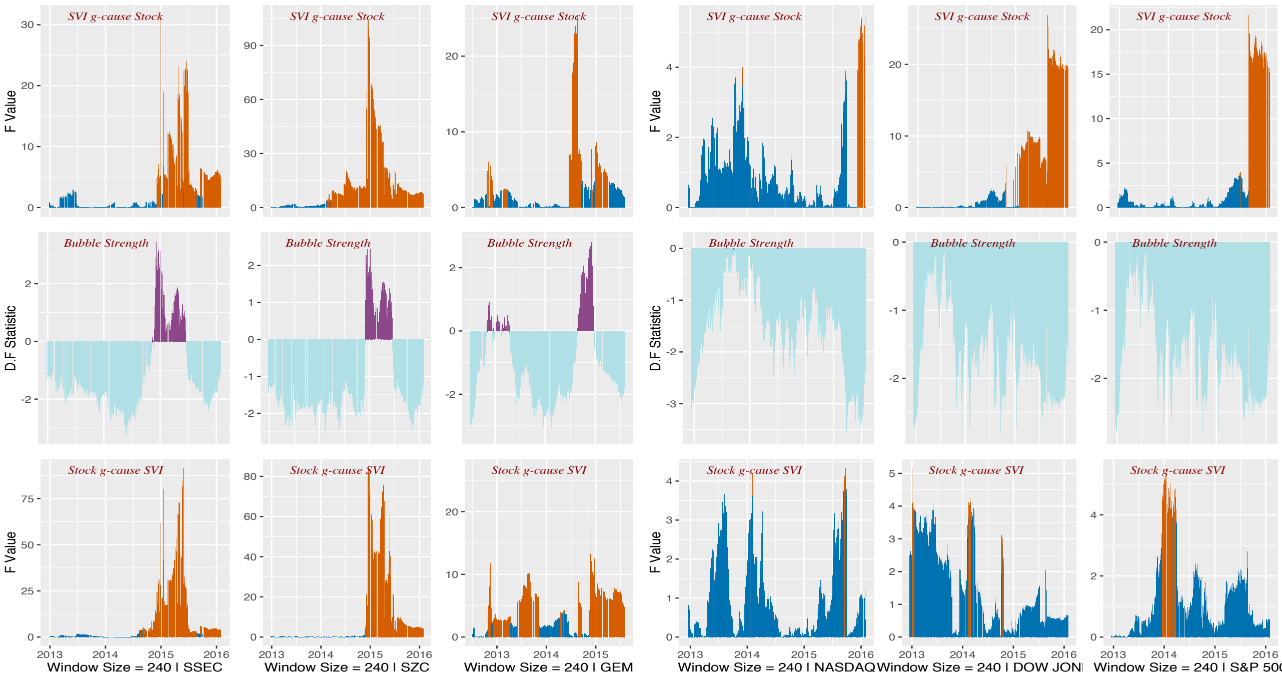
$$\Delta P_t^n = \alpha_p \textstyle\sum_{i=1}^{p} \beta_{pi} \Delta S_t^n + \sum_{j=1}^{n} \delta_{pj} \Delta P_t^p + \varepsilon_t \tag{7}$$

Results

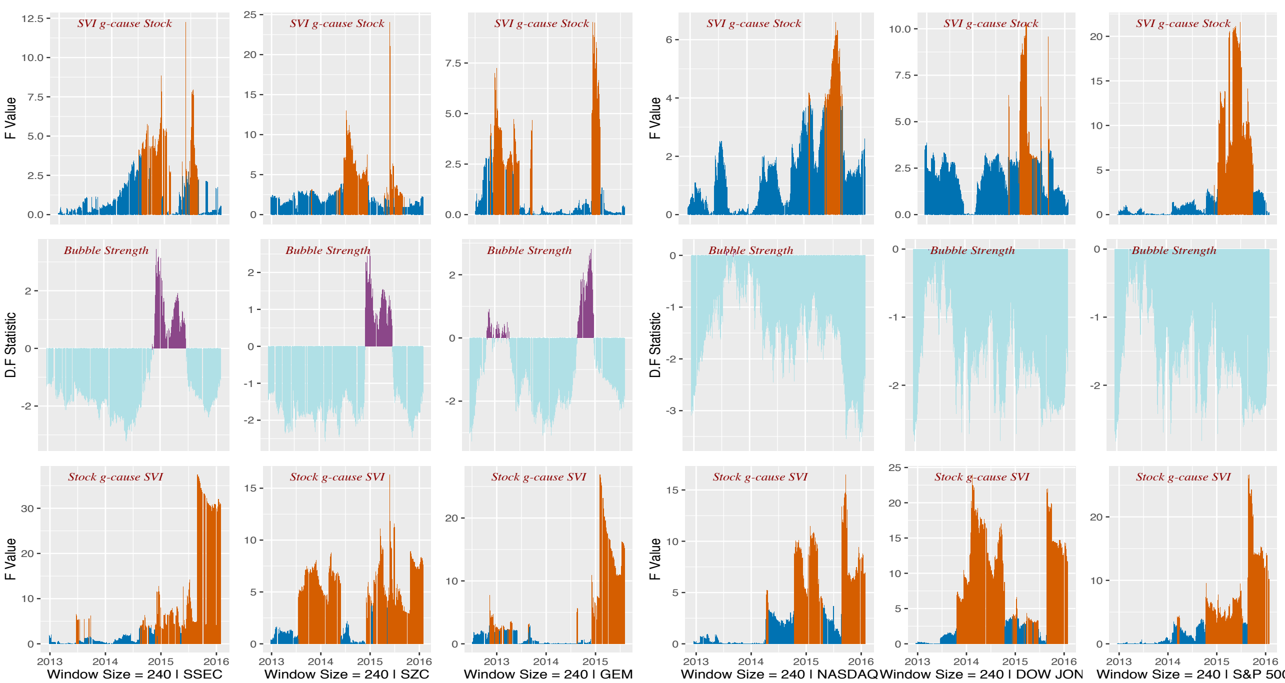
Positive Feedback Test

We find strong evidence of bidirectional Granger causal relations during the bubble period in three markets in Group 1. In the SSEC and the SZC, bidirectional causal relationships are significant only after the market surge. For the SSEC, the Granger causality from stock price to SVI becomes significant earlier than the causality from the SVI to stock price. For the SZC, the Granger causality from SVI to stock price becomes significant earlier than the causality from stock price to SVI. For both the SSEC and the SZC the positive feedback, remains significant after the bubble crash, but the relative strength of the feedback drops sharply with the drop of bubble strength. Indeed, after the bubble crashed in June of 2015, the Chinese government has implemented various policies trying to save the market but failed. Many strong market forces could suppress the collective behavior of individual investors and make the regression results complex. In the GEM, the bidirectional causal relationships are found in both of the bubble periods, and the causality from the SVI to stock prices comes earlier in both cases, however the behavior is less clear than it is in SSEC and SZC.

In contrast, in the whole sample span of Group 2, we have not detected any bubble, and found any period of significant evidence of feedback between the positive stock movement and the positive public attention movement. Therefore, we conclude that the same feedback mechanisms do not exist in non-bubble periods, but the unidirectional transfer function model works well in these periods.(See the section, *Transfer Function Models for the Non-Bubble Periods*, in supplementary files for details.)



(a) Positive Feedback



(b) Negative Feedback

Figure 2. Positive Feedback(the top one) tests and Negative Feedback(the bottom one). Results: in graph (a), the upper graphs are the F-Value to test the significance of Equation 3 and the bottom ones are the F-value to test the significance of Equation 4. The orange lines indicate the causal-significant at each time point while the blue lines are not; in the middle graphs, the purple lines and light cyan lines represent the ADF statistics that measure the strength of market bubble, in which the purple lines specify bubble-significant. Situation are the same in graph (b).

Negative Feedback Test

Following the test results, patterns in the negative feedback test are less regular than those in the positive feedback test(see Fig:2(b)). In Group 1, markets present significant bidirectional causal relationships at the later stage of the measured bubble periods, and there is an absence of the negative feedback in the middle of the bubble in these markets. And for the GEM, unlike the behavior of the second bubble, the negative feedback covers the first bubble period instead of appearing at a later stage. But we have to notice that this explosive process did not actually crash(see the third graph in Figure 1). The higher strength of the positive feedback suppresses the negative feedback in this period and the stock price increases constantly. In Group 2, we also find significant negative feedback in the periods where no bubble presents and this evidence has no relation with market bubble, and we somehow attribute it to the mechanism of spread of market panic and short-term selling behavior.

Discussion

Our test results support the feedback between the public attention and stock prices in the bubble periods. Since it is our first time to test this feedback in market bubbles using SVIs as the proxy, it is necessary for us to present some thoughts regarding the behavior of the web searchers and to explain why the correlation varies so significantly for bubble and non-bubble period and for the detected feedback in the bubble periods.

Firstly, the searchers could be categorized in three groups: Type I, Type II and Type III. Type I searchers are individual investors who have already invested in the market. They collect information regularly to update their investment strategies. Type II searchers are potential individual investors who have plans to enter the market and they collect necessary information from the internet to help their decisions. Their search behaviors will not last long and they will end up as either investors or non-investors. Type III searchers are neither investors (Type I) nor potential investors (Type II). They make queries of the stock-related information on the search engine only occasionally for reasons (e.g., headlines). Type III searchers can become Type II and Type I searchers. As for the three types of searchers, there are constant type-flows among them, and their dynamics is important in the bubble generating process.

Now considering the periods when the market is stable, the activities of Type II and Type III searchers are limited with few motivations, so the search volume will stay stable at a lower level as a reflection of the stable information demands from Type I searchers. In these periods, occasional sharp changes in stock prices could happen and draw more attention from Type II and Type III searchers, but the attention will drop back to its normal level eventually. Based on the rolling ADF test for bubble, we have found that the SVIs are stationary in the non-bubble periods and they become non-stationary when there are bubbles in the markets. Also, for the non-bubble periods we can attribute transfer function models for the SVIs and the change of stock prices. The transfer function models show strong evidence of asymmetrical response of SVIs to the stock price change with different signs. The market fall induces higher increase in SVIs compared with market rise. Then we consider the relationships between the two series when there is a bubble. Type I searchers are likely to increase their search frequency when stock prices keep increasing. Attracted by the expected earnings, more Type II searchers will become Type I and contribute to a higher long-term attention level. Also, the number of Type III searchers will increase because of massive media coverage or suggestions from friends. Therefore, many Type III searchers may become Type II and eventually Type I searchers. In this case, the search volume from all categories will increase because of the increasing stock prices, and there is a flow of searchers from type III to type I. On the other hand, the constantly increasing SVI implies more and more non-investors becoming investors(One fact is that the number of newly opened accounts in Shanghai Security Exchange increases significantly throughout the bubble generation process from late 2014 to middle 2015.), and the stock prices will increase because of higher demands. This fulfills the feedback and the bubble is generated.

On the other hand, individual investors are sensitive to market falls in the bubble periods, which can be triggered by institutional investors massive selling behaviors. In this case, the increased SVI could represent the extra information demand when the searchers are facing market falls and the upcoming uncertainty. Being afraid of further loss, the individual investors would sell their shares, causing the market price to fall, so more attention will be induced and the worries can spread among different types of searchers.

Conclusion

In this paper, a novel measure of public attention the search volume index (SVI) is used to exam the classical hypothesis of feedback generating market bubbles. Having been widely applied in various subjects, the SVI, which reflects the demand of information before decision making, proves its leading role as a measurement of public attention. Typically, the SVIs, in stock market related searches, mostly represent the information needs of the individual investors with herding behavior, who are the major contributor to market bubble generation. Featuring these properties of SVIs of stock markets, the data used in this paper represent the stock markets with significant bubbles after year 2008. The right-tailed rolling ADF test is used to determine bubble and non-bubble periods. When there are no market bubbles, the correlation between SVIs and market prices is low and the SVIs are typically stationery and can be modeled with transfer functions(see supplement). The positive and negative changes of stock prices are the inputs in the transfer functions and affect SVIs asymmetrically.From this perspective, no feedback is regarded as existing in the non-bubble period. As for the bubble periods, in order to present an informative temporal view of the relation between market bubbles and the feedback mechanism, the rolling regression method is utilized and the right-tailed ADF test and the Granger causality test are performed to measure the market bubble strength and the feedback strength accordingly. In the face of temporal representations of the bi-variate relationships, evidence strongly suggests the existence of feedback between the positive changes of the SVIs and the positive changes of stock prices during bubble periods. Negative feedback between the positive changes of SIVs and the negative changes of stock prices found at the later stages of the bubble periods can be attributed to a higher volatility in the later stages of the bubble periods and the crash of the bubbles. For the results, their bi-variate relationships are discussed and analysis is provided for the macro-level behaviors of the SVI based feedback potentials.

This paper is significant in three aspects. Firstly, it is the first time that the classical hypothesis of feedback between public attention and stock price is tested quantitatively at a proxy level. Secondly, this paper filled the vacancy in the previous studies and utilized the search volume index in the study of market bubbles. One of the two types of previous studies used the number of news-papers as one of a few proxy measures to study the correlation between public attention and stock prices in the bubble period, a group of which discussed the potential feedback with experimental evidence and theories from psychology. None was able to dig deep due to the limitation in the attention data[1–13] collection. The other type utilize the SVIs to predict stock prices but failed to cover the bi-variate relationships when bubbles[14–17,19,21]exist in the market. This paper combines two types of previous studies and utilize SVIs in the analysis of stock market bubbles, presenting behavioral patterns new to the previous findings. Thirdly, the results gained in this paper provide more insights into the feedback mechanism during bubble periods. The positive and negative feedback studied in this paper suggest that market bubbles are affected by the two opposite mechanisms and their competition could determine the fate of the bubble. Our conclusions are different from traditional views that positive feedback works in the bubble generation process while negative feedback works in the bubble crash process. Also the results indicate a combined influence of the two types of feedback. In this case, further advanced studies in strength measurement of the feedback and the competition of the feedback may be new tools in financial risk management.

Faced with the extremely complex global financial system, we have only explored a small part of it. However, as more data become available, we will be able to incorporate additional behavioral indices in our models to discover the yet unknown.

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Author contributions statement

Must include all authors, identified by initials, for example: A.A. conceived the experiment(s), A.A. and B.A. conducted the experiment(s), C.A. and D.A. analysed the results. All authors reviewed the manuscript.

Additional information

To include, in this order: **Accession codes** (where applicable); **Competing financial interests** (mandatory statement).
The corresponding author is responsible for submitting a competing financial interests statement on behalf of all authors of the paper. This statement must be included in the submitted article file.

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