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Explosive behavior in the Chinese stock market: A sectoral analysis

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ABSTRACT

This paper examines the existence of explosiveness in the Chinese stock market from a sectoral perspective. To that end, the method recently developed by Phillips and Shi (2019), which is an extension of the standard bubble detection technique of Phillips et al. (2015a,b), is used. The empirical results reveal the presence of several explosivity periods in all equity sectors and the aggregate equity market, showing the high propensity of the Chinese stock market to the appearance of episodes of explosiveness. One possible explanation for this frequent explosive dynamics stems from the fact that the Chinese equity market has numerous unique features and is still in an early stage of development. The two main periods of explosiveness common to many Chinese equity sectors correspond to the well-known 2007 and 2015 Chinese stock market bubbles. However, there seems to be some heterogeneity across sectors in terms of the number and duration of explosivity episodes. Furthermore, the significant degree of co-movement of periods of explosiveness in different equity sectors suggests potential contagion effects of explosive dynamics to the whole Chinese equity market, with the consequent detrimental impact on the Chinese real economy.

1. Introduction

The Chinese equity market is currently the second largest stock exchange in the world only after that of the US. In fact, the joint market capitalization of the two mainland Chinese stock markets (Shanghai and Shenzhen stock exchanges) was around US$ 12.5 trillion at January 2023. Beyond the size, the Chinese equity market possesses a number of features that differentiate it from the stock markets of developed countries (Yao et al., 2019; Leippold et al., 2022). First, unlike the more mature capital markets characterized by the predominance of institutional investors, retail investors have consistently prevailed in the Chinese stock market (Hong et al., 2022).[1] Pension funds and insurance companies, which have a stabilizing effect on the financial markets of developed countries through their buy-and-hold strategies, have played a very minor role in the Chinese financial system. Due to this dominance of small investors, the China's equity market has been frequently compared to a casino. The speculative and short-termism behavior of most inexperienced investors produces increased levels of turnover and market volatility, leading to the disconnection of the Chinese stock market from the reality of economic activity and corporate earnings. Second, Chinese stocks have been traditionally owned by Chinese investors, while overseas investors have faced serious restrictions to invest in China's mainland equity markets. According to a recent

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[1] In particular, at the end of December of 2020 the Shanghai and Shenzhen stock exchanges had 265.39 and 264.53 million retail investors versus 0.80 and 0.63 million institutional investors, respectively, according to the 2020 annual statistics of both stock exchanges.

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report from the Bank of Finland Institute of Emerging Economies (BOFIT, 2023) based on data from the People's Bank of China, overseas investors held about 4% of Chinese listed shares at the end of September 2022 due to the declining trend of the Chinese stock market during 2022, which also contributes to the segmentation from global financial markets. Third, many of the Chinese listed companies are state-owned, which often results in political objectives taking precedence over corporate productivity and shareholder value maximization. Fourth, China is still imposing stringent constraints on short selling, which makes it difficult the rapid correction of overvaluation and hampers the efficient price discovery of Chinese stocks.

This unique institutional background of the Chinese equity market makes it more vulnerable to rumors, imitation, speculation, and herding behavior than other more mature markets. Therefore, the Chinese stock market provides a suitable setting for the analysis of bubbles and market crashes. Against this backdrop, the purpose of this paper is to explore the existence of explosive dynamics in the Chinese equity market at the sectoral level over the last two decades using the model developed by Phillips and Shi (2019). This novel framework is an extension of the standard bubble detection technique put forward by Phillips et al. (2015a, 2015b). The key advantage of the procedure of Phillips and Shi (2019) lies in its capability to generate realistic patterns of price behavior that enable the identification of both market expansions and crises as well as the consistent estimation of the start and end dates of such explosive episodes. Furthermore, this approach reduces the delay bias in the identification of bubbles typically associated with the conventional method of Phillips et al. (2015a, 2015b). In addition, a new composite bootstrap procedure designed by Phillips and Shi (2020) to mitigate potentially severe size distortions caused by heteroskedasticity and multiplicity issues, which are fairly common in recursive testing algorithms, is utilized in this work coupled with the bubble identification model of Phillips and Shi (2019).[2]

This paper makes three relevant contributions to the extant literature on explosivity in stock prices. First, to the best of our knowledge, this is the first study that investigates the presence of explosive behavior in the Chinese equity market at the sectoral level instead of the usual aggregate market level using the approach of Phillips and Shi (2019) combined with the heteroskedasticity- and multiplicity-consistent bootstrap technique of Phillips and Shi (2020). A sector analysis is necessary because market-wide aggregation can mask important differences across sectors with respect to proclivity to explosive dynamics. As stated by Greenwood et al. (2019), many bubbles throughout history, such as the Dot-com bubble of the late 1990s and the real estate boom of the 2000s, have evinced a clear sector component. Given that companies belonging to the same sector are subject to similar risk factors and technological improvements, it seems natural to suppose that the episodes of explosiveness tend to manifest themselves at the sector level. The identification of sectoral heterogeneity in terms of explosive behavior can help investors and portfolio managers make better asset allocation and risk management decisions that prevent large losses caused by the bursting of speculative bubbles. Moreover, policy makers can identify the sectors most prone to explosive behavior and make informed decisions to maintain financial stability. Additionally, the sector-level analysis is less influenced by idiosyncratic risk of individual companies as its results have less noise. Thereby, this paper aims to fill this research gap by providing a comprehensive analysis of the dynamics of explosiveness in the Chinese stock market from a sectoral perspective. Second, by covering a relatively long time span that encompasses the COVID-19 pandemic, this work offers an updated picture of the degree of exposure of Chinese equity sectors to episodes of explosiveness. Third, unlike prior studies on explosive behavior of Chinese stock prices, this paper pays close attention to the presence of co-explosivity in different Chinese equity sectors. This knowledge provides critical information to regulatory authorities about the appropriateness of adopting measures intended to avoid a high systemic risk related to contagion of explosiveness among sectors that can compromise the stability of the Chinese financial system and even endanger China's economic growth.

The empirical findings demonstrate the presence of explosive dynamics in all Chinese equity sectors, corroborating the high propensity of the Chinese stock market to the appearance of explosiveness. The two major periods of explosive behavior common to many Chinese equity sectors coincide with the widely known 2007 and 2015 Chinese stock market bubbles. However, there seems to be some variation across sectors regarding the frequency and length of explosivity episodes. Further, the significant degree of co-movement of explosiveness episodes in different sectors suggests potential contagion effects of explosive dynamics throughout the Chinese equity market, which could ultimately affect the real economy. A plausible explanation for the recurrent explosive dynamics of the China's equity market at the sectoral level in a comparatively short space of time is based on two major reasons. First, the uniqueness of the Chinese stock market, especially with regard to the preponderance of small retail investors with strong short-term speculative trading behavior subject to herding effects, makes it particularly susceptible to the formation of speculative bubbles and their subsequent bursting. Second, the Chinese stock market is still in a nascent stage of development due to its low age compared to more mature Western markets. The evidence presented has broad implications for the Chinese regulatory authorities as it underlines the need to adopt far-reaching measures aimed at achieving a more investment-oriented stock market as well as developing a compelling bubble early warning system that helps prevent the contagion of explosive dynamics among sectors and maintain financial stability.

The remainder of the paper proceeds as follows. Section 2 introduces the concept of asset price bubble and provides a brief review of the most relevant literature on explosiveness in stock prices. Section 3 presents the conceptual and methodological frameworks used to the identification of explosive episodes in the Chinese equity market at the sectoral level, while Section 4 describes the dataset employed in this study. The main empirical results are presented and discussed in Section 5. Finally, Section 6 concludes the paper.

[2] The multiplicity issue in this context refers to that the probability of making false positive bubble detections increases when a test is conducted many times on the same dataset, as is the case of recursive algorithms.

2. Concept of bubble and literature review

The concept of bubble is by no means new in the economic literature, but history provides numerous examples of asset price bubbles beginning with the Dutch Tulipmania in 1636–1637. One of the most widely accepted bubble definitions establishes that a bubble exists when the price of an asset deviates considerably and on a sustained basis from its fundamental value. According to Quinn and Turner (2020), marketability, money and credit, and speculation are the three necessary conditions for a bubble, forming what they call "bubble triangle". Asset price bubbles can have severe economic consequences. On the one hand, bubbles lead to an inefficient allocation of resources as funds are directed towards speculative assets instead of productive companies. On the other hand, bubbles favor irrational trading in asset markets and the emergence of herding behavior in investors, further exacerbating asset price volatility. Additionally, the bursting of the bubbles can end up contaminating the real economy, causing a general decline in economic activity.

The bubble phenomenon has often been linked to stock markets. As stated by Asim et al. (2020), the attraction of investors to certain companies or sectors, fueling intense speculation and a sharp rise in share prices, but which after a while translate into a collapse in stock prices, is a recurring event in stock markets. Throughout history there have been many cases of equity market bubbles, including the French Mississippi company in 1719–1720, the UK South Sea bubble in 1720, the first emerging market bubble in the UK in 1824–1826, the Wall Street crash of 1929, the Dot-Com collapse in 2000 and the global financial crisis in 2008–2009. Motivated by the grave economic implications of bubbles, a plethora of recent empirical studies have examined the existence of speculative bubbles in stock markets at the country level, particularly in the US (Bohl, 2003; Zhang et al., 2016; Basse et al., 2021; Nguyen and Waters, 2022), and also internationally (Demirer et al., 2019; Chen et al., 2021; Hudepohl et al., 2021; Wang et al., 2021). All these works identify a series of periods of exuberance in stock prices over the last four decades that preceded notorious market crashes, such as the Black Monday in October 1987, the 1997 Asian financial crisis, the 2000 Dot-Com bubble burst, the 2007–2008 global financial crisis and the 2015 stock market disaster in China.

Research on stock market bubbles has experienced sizeable advance in recent years in parallel with the development of increasingly sophisticated econometric approaches. Most of the popular techniques for bubble detection build on variants of the conventional Augmented Dickey-Fuller (ADF) unit root test (e.g., Diba and Grossman, 1998; Phillips and Yu, 2011; Phillips et al., 2011).[3] However, the bubble identification procedure of Phillips et al. (2015a, 2015b) (PSY henceforth) is currently the most extensively used approach for detecting exuberance in a wide variety of asset markets. The PSY methodology is based on a right-tailed unit root test and employs a recursive algorithm that allows multiple bubbles to be captured while outperforming various alternative techniques. The key assumption behind this approach is that the exuberant behavior in asset prices, which can be easily detected through recursive testing methods such as right-sided unit root tests, is a primary indicator of the expansionary phase of a bubble. Nevertheless, the analysis of stock price bubbles at the sectoral level has so far received very little attention in the financial literature. In particular, Narayan et al. (2013), Milunovich et al. (2019) and Zhao and Sornette (2021) are the only contributions that have examined the presence and extent of speculative bubbles using sector-level data.

A rapidly growing body of work has explored the bubble phenomenon in Chinese stock prices in recent years. Despite utilizing various methodological approaches, there is a broad consensus on the presence of speculative bubbles in the China's equity market. In a pioneer contribution, Jiang et al. (2010) detected the 2005–2007 and 2008–2009 bubbles in the Shanghai and Shenzhen stock exchanges employing the Log-Periodic Power Law Singularity (LPPLS) model. Subsequently, applying the same methodology, Sornette et al. (2015), Li (2017) and Shu and Zhu (2020) found three episodes of explosiveness in the whole Chinese stock market associated with well-known historical events over the last two decades, namely the Chinese stock bubble in 2005–2007, the stock market bubble of 2008–2009 and the Chinese stock market meltdown of 2014–2015. Similarly, combining the fractal theory and the LPPLS framework, Meng et al. (2020) confirmed the presence of various types of stock price bubbles in China, demonstrating the high propensity of the Chinese equity market to explosive behavior. Using the Backward Supremum ADF (BSADF) statistic over a recent time interval, Wang et al. (2021) disclosed explosive dynamics in Chinese stock prices from September 2014 to June 2015. Likewise, based on the GSADF and BSADF statistics, Li et al. (2021b) discovered multiple bubbles in several Chinese stock markets. In addition, Li et al. (2021a) proposed the Backward Infimum ADF (BIADF) statistic for identifying financial crises and utilized it together with the BSADF statistic. They detected two bubble-led crises in the China's stock market, which correspond to the financial crisis of 2007–2008 and the stock market disaster of 2015. From an alternate perspective, Zhao et al. (2021) investigated the contagion effect between speculative bubbles in the crude oil and Chinese stock markets estimated by the BSADF test employing the Granger causality approach. Their results clearly supported the bilateral contagion of bubbles between both markets.

A common feature of all the above-mentioned papers is that they provide evidence of episodes of explosivity in the overall China's stock market, but without investigating explosiveness at a more disaggregated level. The work most similar to ours is a recent one by Zhao and Sornette (2021), which looks into the presence of industry-level bubbles in both the Chinese and US equity markets. However, that paper differs from ours in at least three aspects. First, Zhao and Sornette (2021) combine the LPPLS model with the event study method, while we use the approach of Phillips and Shi (2019) for the analysis of explosiveness. Second, our study also deviates from Zhao and Sornette (2021) in using a longer time period, which includes the recent COVID-19 pandemic, as well as a different data frequency. Third, unlike Zhao and Sornette (2021), our study explicitly addresses the potential interactions among episodes of explosivity (co-explosivity) in different Chinese equity sectors. Therefore, the present research allows us to gain a more thorough understanding of the explosiveness dynamics in the Chinese stock market, thus enriching the actual knowledge about an emerging

[3] However, it is worth highlighting that the Log-Periodic Power Law Singularity (LPPLS) model proposed by Sornette et al. (1996) has also often been utilized to diagnose stock price bubbles.

market with immense potential, although still quite unknown to many international investors.

3. Conceptual and methodological frameworks

The classical asset pricing model of Lucas (1978) is widely used as the theoretical foundation of the bubble testing literature (Basse et al., 2021). Next, we present a brief conceptual framework centered on this model to illustrate the idea of bubble identification. Under the no-arbitrage condition, the price of any asset can be calculated as follows:

$$P_t = \frac{1}{(1+r_t)} E_t[P_{t+1} + D_{t+1}] \tag{1}$$

where P_t denotes the observed price of the asset at time t, r_t is the positive discount rate, D_{t+1} refers to the future payoff received from the asset, and $E_t[\bullet]$ is the conditional expectation operator with respect to the information set Ω_t available at time t.

The application of recursive substitution to Eq. (1) up to period k yields the following decomposition:

$$P_t = \sum_{i=1}^{k} \frac{1}{(1+r_t)^i} E_t[D_{t+i}] + \frac{1}{(1+r_t)^k} E_t[P_{t+k}] = F_t + B_t \tag{2}$$

where F_t and B_t are the fundamental and bubble components of the asset price, respectively. As can be seen, the fundamental component simply represents the present value of expected future payoffs, while the bubble component satisfies the following sub-martingale property:

$$E_t[B_{t+1}] = (1+r_t)B_t \tag{3}$$

If the transversality condition $\lim_{k\to\infty} E_t\left[(1+r_t)^{-k}P_{t+k}\right] = 0$ holds, then in absence of bubbles ($B_t = 0$) the asset price equals the fundamental component, which behaves like a martingale process. Otherwise, the asset price exceeds the fundamental for $B_t > 0$ and exhibits an explosive behavior caused by the submartingale property of the bubble component. This means that the asset price decouples explosively from the fundamental component. Accordingly, the basic approach for detecting bubbles in asset prices is to test against explosiveness.

Based on the Lucas' pricing model, a number of econometric methods, with predominance of recursive right-tailed unit root tests, have been put forward to identify bubbles in asset prices (i.e., Diba and Grossman, 1988; Phillips and Yu, 2011; Phillips et al., 2011; Phillips et al., 2015a, 2015b). In this regard, the PSY procedure introduced by Phillips et al. (2015a, 2015b) has become the most popular and influential framework for detecting explosive behavior associated with bubbles. The PSY approach relies on the recursive application of a right-tailed ADF unit root test over changing subsample regressions. The central idea behind this method is to utilize ADF-style regressions that switch the start and end dates of a rolling window to capture more precisely any explosive dynamics. Although the PSY procedure was originally designed for identifying speculative bubbles, recently Phillips and Shi (2019, 2020) have shown that this approach has capacity to detect both exuberance periods and market crashes as the PSY algorithm can be extended to cover market collapse dynamics (Enoksen et al., 2020). Thereby, the refined version of the PSY procedure developed by Phillips and Shi (2019) is used in this study to explore the presence of explosive dynamics in the China's stock market at the sectoral level. The improved framework of Phillips and Shi (2019) is able to generate realistic patterns of price behavior during abrupt crisis episodes and is, therefore, particularly well-suited for capturing market collapses.

Specifically, Phillips and Shi (2019) extend the data generating process (DGP) to adequately reflect disruptive market crashes. Specifically, they model the dynamics of asset prices during market collapses as a random drift martingale process given by:

$$logP_t = -L_t + logP_{t-1} + u_t \tag{4}$$

where u_t are martingale difference sequence innovations and L_t denotes a random sequence term independent of u_t and temporarily and locally asymmetric in the negative direction. The sequence L_t generates a random drift in the observed asset and is the cause of the appearance of the collapse dynamics. L_t can take different forms, which lead to a variety of realistic crisis trajectories that are not necessarily monotonic. Phillips and Shi (2019) assume that L_t follows an asymmetric scaled uniform distribution such that:

$$L_t = Lb_t, \sim_{iid} U[-\epsilon, 1], 0 < \epsilon < 1 \tag{5}$$

where L is a positive scale quantity that measures the shock intensity and b_t is uniform on an interval ranging from a typically small negative value $-\epsilon$ to unity. This collapse process exhibits an overall downward trend whose magnitude depends on the values of the scalar parameters L and ϵ.

The identification of a market crash is achieved by testing the null hypothesis of normal market behavior (martingale process with a mild drift as in the standard PSY procedure) against the alternative of market crash (random drift martingale process). Thus, under the normal market conditions delimited by the null hypothesis, the scale parameter L is zero and the asset price follows a martingale with an asymptotically negligible drift, which formally can be written as:

$$logP_t = cT^{-\eta} + logP_{t-1} + u_t \tag{6}$$

where c is a constant, T denotes the sample size and localizing parameter $\eta > 1/2$.

In contrast, under the market collapse state delimited by the alternative hypothesis, the asset price exhibits a collapse dynamics with DGP identical to that described by Eq. (4). Additionally, it should be noted that the null (martingale process with a mild drift) and alternative (mildly explosive process) hypotheses during bubble periods are exactly the same than those considered by the standard PSY procedure of Phillips et al. (2015a, 2015b).

The reduced form ADF-type regression model employed for the PSY approach can be written as follows:

$$\Delta P_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} P_{t-1} + \sum_{j=1}^{p} \phi^j_{r_1,r_2} \Delta P_{t-j} + \varepsilon_t \tag{7}$$

where Δ stands for the first difference operator, p denotes the lag order of the model to control for potential serial correlation and ε_t is an *i.i.d.* error term with zero mean and constant variance. α_{r_1,r_2}, β_{r_1,r_2} and $\phi^j_{r_1,r_2}$ are parameters estimated by OLS, being β_{r_1,r_2} the main parameter of interest. In turn, r_1 and r_2 are the fractions of the total sample T representing the starting and ending points of a given subsample, while r_0 denotes the minimum window size required to initialize the computation of the ADF statistic. The ADF statistic corresponding to the subsample running from r_1 to r_2, denoted by $ADF^{r_2}_{r_1}$, is simply the t-statistic of the OLS estimate of β_{r_1,r_2} and can be calculated as:

$$ADF^{r_2}_{r_1} = \frac{\widehat{\beta}_{r_1,r_2}}{s.e.\left(\widehat{\beta}_{r_1,r_2}\right)} \tag{8}$$

where $s.e.(\bullet)$ represents the standard error of the estimated parameter $\widehat{\beta}_{r_1,r_2}$.

The null hypothesis of the PSY procedure ($\beta_{r_1,r_2} = 0$) assumes that asset prices follow a random walk process and thus contain a unit root, whereas the alternative hypothesis ($\beta_{r_1,r_2} > 0$) implies that asset prices behave explosively. If the null hypothesis is rejected, the Backward Supremum ADF (BSADF) statistic can be used to consistently date-stamp the origination and termination dates of each explosive process as it offers further flexibility in the detection of multiple explosive episodes. Mathematically, the BSADF statistic is defined as the supremum value of the ADF statistics calculated over all feasible ranges of r_1 and r_2:

$$BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} ADF^{r_2}_{r_1} \tag{9}$$

The BSADF statistic is recursively implemented on backward expanding samples, in such a way that the end point of the regression, r_2, is fixed and the starting point, r_1, is allowed to vary between 0 and $r_2 - r_0$. By varying the ending fraction r_2, a sequence of BSADF statistics is obtained, from which it is possible to determine the starting and ending points of each explosive process. The presence of explosive dynamics is tested by comparing the BSADF statistic with the heteroskedasticity and multiplicity-adjusted critical values derived from the bootstrap procedure of Phillips and Shi (2020). As previously indicated, this composite bootstrap technique simultaneously addresses both heteroskedasticity and multiplicity issues in recursive testing procedures, thus reducing the probability of spurious bubble detection.[4]

The date-stamping strategy recommended by Phillips et al. (2015a) based on the sequence of BSADF statistics establishes that the estimated origination and termination dates of a period of explosiveness are, respectively, given by:

$$\widehat{r}_e = \inf_{r_2 \in [r_0, 1]} \left\{ r_2 : BSADF_{r_2} > cv^{\alpha_T}_{r_2} \right\} \tag{10}$$

$$\widehat{r}_f = \inf_{r_2 \in [\widehat{r}_e, 1]} \left\{ r_2 : BSADF_{r_2} < cv^{\alpha_T}_{r_2} \right\} \tag{11}$$

where $\widehat{r}_e$ and $\widehat{r}_f$ denote the origination and termination dates and $cv^{\alpha_T}_{r_2}$ represents the $100(1-\alpha_T)\%$ critical value (quantile of the distribution) of the BSADF statistic resulting from the bootstrap method of Phillips and Shi (2020), being α_T a real number between 0 and 1 that indicates the significance level of the test. In other words, the origination date of a bubble is the first chronological observation whose BSADF statistic exceeds its corresponding critical value. Likewise, the end point can be defined as the first chronological observation where the BSADF statistic falls below the critical value.

Once the episodes of explosiveness are properly identified and date-stamped, it can be interesting to investigate the presence of co-explosivity (Bouri et al., 2019). In the context of the present study, the basic idea is to figure out if the explosive behavior in a certain Chinese equity sector tends to be accompanied by explosive dynamics in other sectors. Logistic regression offers a simple but effective framework to assess whether periods of explosivity occur simultaneously in various equity sectors. This approach allows modelling the probability of appearance of explosiveness in a sector as a function of the occurrence of episodes of explosivity in the remaining sectors. Accordingly, the following logistic regression model can be used to formally evaluate the existence of co-explosivity:

[4] More technical details on the implementation of this novel bootstrap procedure can be found in the original paper by Phillips and Shi (2020).

Table 1
Average weight of Chinese equity sectors.

Industry	Average weight
Financials	31.93%
Industrials	15.81%
Materials	10.96%
Consumer Discretionary	9.43%
Consumer Staples	8.34%
Information Technology	7.27%
Energy	5.09%
Health Care	4.98%
Utilities	3.91%
Real Estate	3.22%
Telecommunication	1.49%

Note: This table shows the average weight of each of the eleven selected equity sectors in the overall Chinese stock market over the period from January 2005 to December 2022 based on end-year data collected from the Chinese WIND Economic Database.

Table 2
Summary statistics of Chinese sector and aggregate equity indexes.

Sector	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Financials	8.36	9.13	6.78	0.50	−1.54	2.08	526.28***
Industrials	7.71	8.57	6.70	0.37	−0.65	0.59	78.46***
Materials	7.72	8.74	6.65	0.40	−0.42	0.44	33.58***
Consumer Discretionary	8.24	9.22	6.67	0.55	−1.15	1.06	245.01***
Consumer Staples	8.93	10.69	6.81	0.89	−0.20	0.00	6.23**
Information Technology	7.44	8.23	6.44	0.37	−0.45	−0.31	34.93***
Energy	7.65	8.92	6.69	0.44	0.46	−0.20	33.52***
Health Care	8.63	9.91	6.69	0.75	−0.97	0.60	156.53***
Utilities	7.44	8.20	6.68	0.30	−0.31	0.14	15.35**
Real Estate	8.50	9.36	6.66	0.60	−1.37	1.49	370.71***
Telecommunication	7.72	8.49	6.68	0.36	−1.11	0.99	226.29***
CSI 300	7.99	8.67	6.71	0.43	−1.23	1.28	294.51***

Note: This table presents the summary statistics of weekly Chinese sector and aggregate equity indexes (expressed in natural logarithm form) over the full sample period (January 2005 to December 2022). Std. Dev., Max and Min indicate the standard deviation, maximum value and minimum value, respectively. As usual, *, ** and *** denote rejection of the null hypothesis of normality at the 10%, 5% and 1% significance levels, respectively.

$$log\left(\frac{P(Y_i = 1|X)}{1 - P(Y_i = 1|X)}\right) = \beta_0 + \beta_j X_{j,t} + \epsilon_t \tag{12}$$

where the dependent variable is a dummy variable Y_i that takes the value of one if $BSADF_{r_{2,t}} \geq cv_{r_{2,t}}^{\alpha_T}$, that is, when there is evidence of explosiveness in the *i*th Chinese equity sector at time *t*, and zero otherwise. In addition, β_0 is a constant, β_j denotes the vector of logistic regression coefficients, while $X_{j,t}$ stands for the vector of dummy variables, $j = 1,2,\ldots,10$. Each one of these dummy variables indicates the presence of explosive behavior, defined exactly in the same way as for the dependent variable, in one of the remaining ten Chinese equity sectors. Lastly, ϵ_t is the error term, assumed to follow a standard logistic distribution.

4. Dataset

The dataset used in this study consists of weekly closing prices of eleven Chinese equity sector indexes and the CSI 300 stock market index, which acts as a proxy for the aggregate Chinese stock market.[5] Specifically, the Chinese equity sectors considered are Financials, Industrials, Materials, Consumer Discretionary, Consumer Staples, Information Technology, Energy, Health Care, Utilities, Real Estate, and Telecommunication, which cover most of the overall Chinese stock market. Limited by the availability of data of the Chinese equity market, the sample period runs from January 7, 2005 to December 30, 2022, totaling 916 weekly observations. This time frame encompasses a number of major national and international events, such as the global financial crisis of 2008–2009, the Chinese stock market meltdown of 2015 and the COVID-19 outbreak at the beginning of 2020. All stock market indexes are denominated in Renminbi and collected from Bloomberg. Following the usual practice in the bubble-related literature, natural logarithms of stock

[5] The CSI 300 is a capitalization-weighted stock market index that tracks the performance of 300 top stocks listed on the two main stock exchanges in mainland China (Shanghai and Shenzhen) and is widely recognized as a good indicator of the general Chinese stock market. The CSI 300 index is calculated since April 8, 2005.

Fig. 1. Episodes of explosiveness in the Chinese stock market at the sector level.
Note: The solid blue lines in the graphs of this figure show the time evolution of the logarithmic closing price of the eleven Chinese equity sectors and the aggregate Chinese equity market (proxied by the CSI 300 index) between January 2005 and December 2022. The green shaded areas denote the

episodes of explosivity with a minimum duration of three weeks detected using the method of Phillips and Shi (2019) and represent the time intervals where the BSADF statistic exceeds the 95% bootstrapped critical value. The bootstrapped critical values are obtained from the heteroskedasticity- and multiplicity-robust bootstrap procedure of Phillips and Shi (2020) using 999 bootstrap replications. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

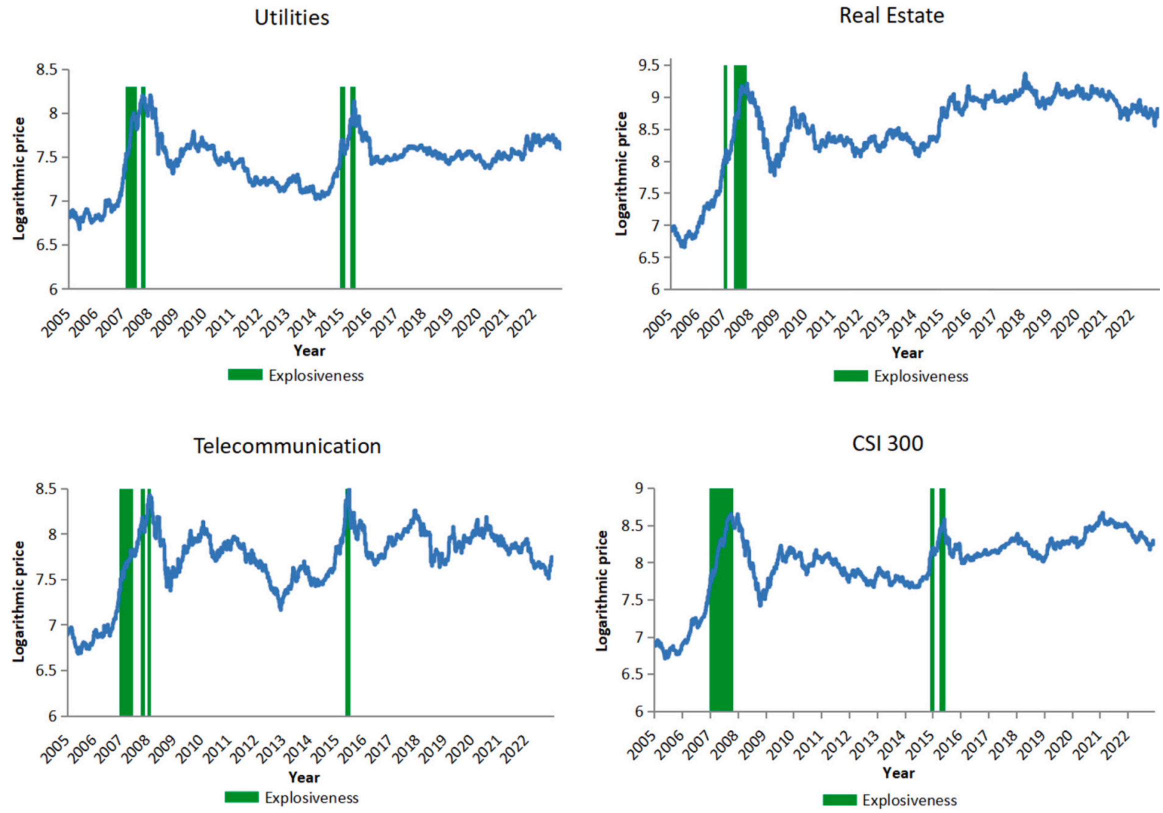

Fig. 1. (*continued*).

market indexes are used for the identification of explosiveness.

Table 1 reports the average weight of the eleven selected equity sectors in the aggregate Chinese equity market over the sample period 2005–2022 based on information compiled from the WIND Economic Database. Interestingly, Financials and, to a lesser extent, Industrials and Materials are the sectors with the largest relative importance in the Chinese stock market during the period under scrutiny. Likewise, it is worth noting the low average weight of the Real Estate and Telecommunication sectors in the broad Chinese market.

Table 2 provides the descriptive statistics of weekly sectoral and aggregate Chinese stock indexes for the entire sample period. Interestingly, the largest volatility, measured by the standard deviation, is, by far, found in the Consumer Staples and Health Care sectors, while the lowest variability is observed in the Utilities and Telecommunication sectors. The skewness coefficient is negative for almost all time series (excepting the Chinese Energy sector), suggesting a greater probability of negative returns compared to the normal distribution. Further, the kurtosis values deviate notably from those of the normal distribution in many cases, indicating leptokurtic behavior. This departure from normality is confirmed by the Jarque-Bera test statistics, which reject the null hypothesis of normality for all Chinese stock price indexes at least at the 5% significance level.

5. Empirical results

This section presents the empirical results of the application of the method of identification of explosive behavior of Phillips and Shi (2019) on the Chinese stock market at the sectoral level. As suggested by Phillips et al. (2015a), to reduce the probability of size distortion, the minimum size of the window, r_0, is set according to the rule of thumb $0.01 + 1.8/\sqrt{T}$, where T is the total sample length. The minimum window size in our sample is 0.0703, which corresponds to 63 weekly observations (sample size $T = 891$ weeks). In turn, the optimal lag order of the ADF model in Eq. (7) is chosen according to the Bayesian information criterion (BIC) with a maximum lag order of 6 for each subsample. The selected lag order is 1 for all the equity sectors and the overall Chinese market, with the only exception of a lag of 3 for the Materials sector. The composite bootstrap procedure of Phillips and Shi (2020) is used to obtain robust finite-sample critical values. The BSADF statistics are compared with the 95% bootstrapped critical values generated from 999 replications. Following Phillips and Shi (2019), the empirical size is controlled over a 104-week period (2 years). The empirical identification of periods of explosiveness in the Chinese equity sectors is carried out using the *psymonitor* R package developed by Caspi et al. (2018), which employs the optimized recursion of Phillips and Shi (2020).

Fig. 1 plots the evolution over time of the logarithmic closing price of the Chinese equity sectors and the aggregate Chinese equity market (proxied by the CSI 300 index) along with the identified periods of explosivity with a minimum duration of three weeks (represented by the green shaded areas) based on the procedure of Phillips and Shi (2019). All Chinese sectors and the entire China's stock market have undergone several episodes of explosiveness over the sample period, although there is variation among sectors in terms of the intensity, exact location and lifetime of such episodes. In this regard, the evidence of explosive behavior seems to be particularly marked in the Materials and Industrials sectors as well as the whole Chinese equity market. On the contrary, Information Technology, Energy and Consumer Staples show up as the Chinese equity sectors least prone to the appearance of persistent explosive dynamics. Moreover, from visual inspection of this figure, it seems evident that there is a certain degree of co-movement of explosiveness episodes across Chinese equity sectors.

Two principal periods of collective explosivity are identified at the Chinese sectoral level. The first and most important period of exuberance occurred basically between the end of 2006 and the end of 2007 and involved nearly all Chinese equity sectors, especially Financials, Industrials, Materials, Consumer Discretionary, Energy, Health Care, Utilities, Real Estate, and Telecommunication, as well as the broad Chinese stock market. This explosive dynamics common to many sectors, although with varying origination and termination dates, can be linked to the Chinese stock bubble of 2007. As a matter of fact, the CSI 300 index reached a record high on October 16, 2007, registering an extraordinary growth of almost 315% in just one year. Certainly, this episode of general exuberance does not appear to have its origin in any particular sector, but was generated almost simultaneously in multiple sectors spurred by a combination of China-specific circumstances. Firstly, the China Securities Regulatory Commission (CSRC), which is the regulator or the Chinese stock market, promoted a series of reforms, such as the non-tradable shares reform and the update of the Company Law and the Securities Law, to boost the sustained and robust development of capital markets. These improvements strengthened investors' trust and made stock investment more appealing. Secondly, the China's vigorous and rapid economic growth in the mid-2000s offered great opportunities both for the expansion of companies and for investors in search of high profits, which also fueled the boom in the Chinese stock market. Notably, during 2006 and 2007 the annual GDP growth rate was above 10% and the Chinese Purchasing Managers' Index (PMI) remained above 50 for all months.[6] Thirdly, the China's exchange rate reform in 2005 led to a sharp appreciation of the Renminbi, making Renminbi-denominated assets more appealing to global investors. Likewise, the Qualified Foreign Institutional Investor (QFII) program launched in 2002 allowed certain licensed international investors to trade directly on China's stock exchanges. Lastly, and more importantly, the singular economic psychology of Chinese retail investors was essential for the formation of the Chinese stock bubble in 2007. As argued by Yao and Luo (2009), greed, envy and speculation are three key psychological factors for Chinese small investors that push their irrational and herding behavior and acted as a catalyst for the creation of the 2007 Chinese stock boom. After peaking in October 2007, the CSI 300 index fell >72% in less than one year.

A widely accepted investment-based explanation for the bursting of the 2007 Chinese bubble focuses on the overvaluation and fundamental weaknesses of many listed Chinese companies, mainly large state-owned firms, as well as the lack of further investment capital. However, three opposite economic psychological factors to those mentioned above also played a crucial role. Concretely, fear, lack of confidence and disappointment of Chinese investors after the initial burst of the bubble aggravated the bearish market performance and led to deeper undervaluation of share prices and a longer lasting market depression. It should be mentioned that several papers, including Jiang et al. (2010), Li (2017), Shu and Zhu (2020), Meng et al. (2020) and Li et al. (2021a), also provide evidence of explosive behavior in the broad Chinese equity market during the year 2007 using a variety of empirical approaches.

The second period of explosiveness took place between early 2015 and mid-2015 and affected all Chinese equity sectors, with the sole exception of the Energy and Real Estate sectors, as well as the aggregate Chinese stock market. Again, this explosive behavior is not clearly attributable to any specific equity sector, but seems to respond to a climate of general euphoria that benefits the stock market as a whole. Thus, the CSI 300 index experienced an astonishing increase of >67% between December 12, 2014 and its peak on June 12, 2015, and then plunged by >43% to its lowest level on August 26, 2015. This episode, popularly known as the 2015 Chinese stock market disaster, originated in a strongly bullish stock market fueled by the confluence of several mutually reinforcing processes. First, the Chinese government actively encouraged Chinese people to participate in the China Dream through the stock market, promising a steady and lasting bull run in stock prices. Second, the policy of diversification of the shareholding structure of the state-owned enterprises (SOEs) promoted by the Chinese authorities to achieve a mixed-ownership economy. Third, the loose monetary policies conducted by the People's Bank of China, characterized by successive cuts in official interest rates in a short interval of time, that increased the appetite of investors for higher-yielding investments such as stocks. Fourth, and no less important, the massive influx into the stock market of new enthusiastic retail investors, with little financial knowledge, low level of risk aversion and often using borrowed money to buy equities (margin trading). The highly speculative nature of Chinese small investors, many of whom seek short-term gains through changes in share prices and are more influenced by herding behavior than company fundamentals, added more fuel to the fire of this stock boom.

Furthermore, a number of factors contributed to the bursting of the Chinese stock market bubble in the summer of 2015. Since the beginning of 2015, China PMI dropped below 50, showing signs of declining growth in the Chinese economy as well as a significant divergence between the stock market and economic fundamentals. Also, international capital flows started to move away from China

[6] The Purchasing Managers' Index (PMI) is a leading indicator of the economic health of the Chinese manufacturing sector. Chinese investors pay great attention to the PMI and make investment decisions based on the new release of the PMI.

Table 3
Origination and collapse dates of periods of explosivity in the Chinese equity sectors.

Financials	Industrials	Materials	Consumer Discretionary
2006:M11–2007:M02	2007:M02–2007:M10	2007:M01–2007:M11	2007:M02–2007:M06
2007:M04–2007:M06	2014:M12–2015:M01	2008:M10–2008:M11	2007:M07–2007:M09
2007:M07–2007:M09	2015:M03–2015:M06	2015:M04–2015:M06	2015:M03–2015:M06
2014:M12–2015:M01			
Consumer Staples	Information Technology	Energy	Health Care
2006:M4–2006:M07	2007:M04–2007:M05	2007:M04–2007:M06	2007:M04–2007:M09
2007:M01–2007:M01	2008:M10–2008:M11	2007:M07–2007:M11	2015:M04–2015:M06
2015:M05–2015:M06	2015:M03–2015:M06		
2017:M10–2017:M11			
Utilities	Real Estate	Telecommunication	CSI 300
2007:M02–2007:M06	2006:M12–2007:M01	2006:M12–2007:M05	2006:M12–2007:M11
2007:M08–2007:M10	2007:M05–2007:M10	2007:M09–2007:M11	2014:M12–2015:M01
2014:M12–2015:M01		2007:M12–2008:M01	2015:M04–2015:M06
2015:M04–2015:M06		2015:M04–2015:M06	

Note: The entries in this table provide the origination and termination dates of episodes of explosivity (no shorter than three weeks) identified for each Chinese equity sector and the whole Chinese stock market using the procedure of Phillips and Shi (2019) along with the heteroskedasticity- and multiplicity-robust bootstrap technique of Phillips and Shi (2020).

Table 4
Descriptive statistics for episodes of explosiveness.

Sector	# of explosive episodes	# of explosive weeks	Duration			
			Mean	Minimum	Maximum	St. Dev.
Financials	7	44	6.29	2	13	4.39
Industrials	5	58	11.6	1	35	13.92
Materials	4	55	13.75	4	41	18.17
Consumer Discretionary	6	47	7.83	1	20	7.55
Consumer Staples	10	29	2.9	1	5	1.60
Information Technology	4	25	6.25	1	13	4.99
Energy	5	28	5.6	1	14	6.39
Health Care	6	40	6.67	1	15	6.09
Utilities	6	48	8	2	19	6.23
Real Estate	5	32	6.4	1	22	9.10
Telecommunication	8	46	5.75	1	14	4.74
CSI 300	4	63	15.75	1	43	18.64

Note: This table provides descriptive statistics for the episodes of explosiveness detected in Chinese equity sectors and the aggregate Chinese stock market (proxied by the CSI 300 index) using the procedure of Phillips and Shi (2019). Specifically, # of explosive episodes denotes the number of explosive episodes, # of explosive weeks is the number of weeks that have explosive behavior, mean indicates the mean duration (in weeks) of explosive periods, minimum and maximum are the minimum and maximum duration of explosivity periods, and St. Dev. is the standard deviation of the duration of episodes of explosiveness.

and many large stockholders began to sell for profit and/or to open short positions in stocks, facilitating the Chinese stock market trend reversal. Additionally, the CSRC became more concerned about the enormous leverage of investors and limited margin financing and short selling activities in mid-June 2015, which amplified the selling pressure of Chinese investors and triggered the stock collapse. Additionally, some inappropriate measures, such as the frequent IPOs, which weaken the market's bullish momentum, and the fuse mechanism (or automatic suspension mechanism), which can create a sense of panic among investors, pushed the bubble burst as well. This evidence of explosive behavior at the sectoral level during 2015 is in line with the findings of Sornette et al. (2015), Shu and Zhu (2020), Li (2017), Meng et al. (2020), Li et al. (2021a), Li et al. (2021b) and Wang et al. (2021) for the aggregate Chinese stock market.

Interestingly, there is no widespread explosive behavior at the sector level in the Chinese stock market during the global financial crisis of 2008–2009. Specifically, episodes of explosiveness at the end of 2008 were only detected in a few Chinese equity sectors, such as Materials and Information Technology, and all of them are characterized by a very short duration. This result is not at all surprising if one takes into account that the Chinese stock market had bottomed out at the end of September 2008 as a result of the bursting of its own bubble prior to the start of the global financial crisis. Similarly, the worldwide financial turmoil triggered by the outbreak of the COVID-19 pandemic in March 2020 had very little impact on the Chinese stock market. As a matter of fact, no Chinese equity sector or the aggregate Chinese equity market show any signs of explosive dynamics during the COVID-19 crisis. These findings confirm the decoupled nature of the Chinese stock market from the international stock markets, presumably due to its unique features previously discussed. Thus, the Chinese market appears to follow its own dynamics driven by the predominance of speculative retail investors and strong State influence and, as a result, remains relatively isolated from major global shocks such as the 2007–2008 global financial crisis or the recent pandemic. The identification of 2007 and 2015 as the two key periods of collective and highly synchronized sectoral explosiveness in the Chinese stock market is entirely consistent with the evidence reported by Zhao and Sornette (2021) in their analysis based on Chinese industry groups. These authors grant an essential role in this finding to the strong herding behavior in the

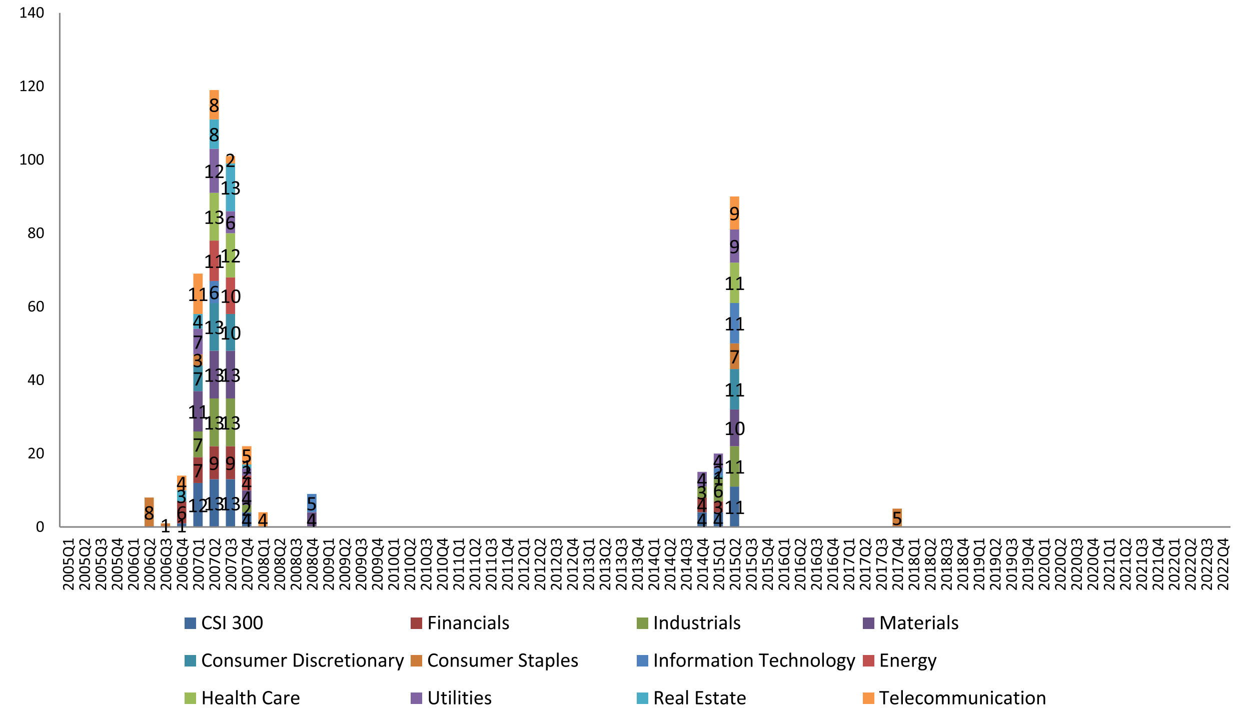

Fig. 2. Episodes of explosiveness per quarter.
Note: This figure shows the episodes of explosiveness, including their duration in weeks, identified by quarter for each Chinese equity sector and the aggregate Chinese stock market (CSI 300) over the entire sample period using the procedure of Phillips and Shi (2019). Each episode is no shorter than 3 weeks. Each sector and the broad stock market are represented by a different color.

whole China's stock market.

The origination and termination dates of episodes of explosiveness with a minimum duration of three weeks for all Chinese equity sectors and the overall Chinese equity market are presented in Table 3. These episodes are identified using the procedure of Phillips and Shi (2019) incorporating the heteroskedasticity- and multiplicity-consistent bootstrap technique of Phillips and Shi (2020). The information reported in this table corroborates that the explosive behavior in Chinese stock prices arises primarily in 2007 and 2015. As can be seen, the explosive dynamics associated with 2007starts at the beginning of the year and ends in October or November 2007 for most of the Chinese equity sectors. This finding suggests that the explosive behavior observed in 2007 does not appear to originate in any specific sector in isolation, but instead plays out simultaneously across multiple sectors. Similarly, the explosiveness corresponding to the year 2015 begins in March or April and ends in June of that year for the vast majority of Chinese sectors, once again showing that the explosive dynamics in the Chinese stock market tend to develop in parallel in many sectors.

Table 4 displays some descriptive statistics for the identified episodes of explosiveness over the entire sample period. As can be noted, all Chinese equity sectors as well as the overall Chinese stock market exhibit several periods of explosivity. However, there is a significant disparity between sectors with regard to the number and duration (in weeks) of such episodes. More specifically, the number of explosivity episodes fluctuates between 4 for the Materials sector and 10 for the Consumer Staples sector. Also, the number of weeks that exhibit explosive behavior ranges from 25 for the Information Technology sector to 58 for Industrials. In addition, the mean duration of the explosive periods varies between slightly <3 weeks and almost 14 weeks, with a maximum duration of 41 weeks detected in the Materials sector. Likewise, there is a notable variation across sectors regarding the standard deviations of the duration of episodes of explosiveness. In particular, the lowest variability is found in the Consumer Staples sector, while the largest variability is observed in the Materials sector. In short, the information provided by this table confirms the strong propensity of the China's equity market to explosiveness in stock prices while revealing the marked heterogeneity across Chinese equity sectors in terms of explosive behavior. Thus, Materials and Industrials are identified as the two sectors most prone to persistent explosive dynamics. In contrast, Energy, Information Technology and Consumer Staples appear as the sectors least vulnerable to the appearance of lasting episodes of explosiveness.

To get a more visual representation of the major periods of explosivity at the sectoral level and following Maouchi et al. (2022), Fig. 2 depicts the episodes of explosiveness (with a minimum duration of three weeks) per quarter for each Chinese equity sector and the aggregate Chinese market identified using the method of Phillips and Shi (2019). The examination of this figure shows one more time that the sector-level explosive dynamics is concentrated in two time intervals, i.e., 2007 and 2015, which concur with the Chinese stock bubble of 2007 and the 2015 Chinese stock market plunge, respectively. In particular, the highest number of explosivity periods is found in the second and third quarters of 2007 and the second quarter of 2015. As one can see, the explosive behavior in both periods affects most of the Chinese equity sectors, although there are differences among sectors in the duration and frequency of explosivity

Table 5
Analysis of co-explosivity between Chinese equity sectors.

	Financials	Industrials	Materials	Consumer Discretionary	Consumer Staples	Information Technology	Energy	Health Care	Utilities	Real Estate	Telecommunication
Financials	–	4.16	−6.69	38.41***	1.00	−14.93**	−2.93	−28.56***	6.23	7.78**	−6.40*
Industrials	27.54***	–	12.21	20.21*	−10.08*	−3.09	−20.50**	−14.68**	14.94**	−13.87**	−7.93*
Materials	14.68**	42.56***	–	2.1	−1.58	−13.69**	−19.17***	−12.87**	2.45	−5.61	−9.75***
Consumer Discretionary	17.40***	24.95**	−2.77	–	−2.42	3.15	−13.21 **	−9.91 **	5.02	−8.44	−10.43 ***
Consumer Staples	−0.04	1.15	−2.73	10.96*	–	0.79	−1.81	−9.29***	−4.66	−0.86	6.99**
Information Technology	17.36 ***	18.82*	−4.80	−12.15*	−4.13	–	−4.85	7.59*	4.90	−15.73***	−2.52
Energy	11.67	−27.19	21.72	10.91	0.02	−7.97	–	−8.53	40.32 **	−10.07	−28.32 ***
Health Care	17.39*	54.41***	−7.16	0.90	−12.59*	17.22	−3.17	–	−25.63*	−13.27	−24.51***
Utilities	30.07***	25.89**	3.76	22.32*	−10.63**	−12.96	−12.98*	−8.26	–	−26.05***	−10.08*
Real Estate	13.41*	13.27	−4.15	32.84*	−0.84	−10.21	0.31	−22.49**	−8.12	–	−18.45**
Telecommunication	14.59**	18.96*	−8.20	13.60	3.87	−1.83	−1.08	−16.39***	−4.45	−14.17**	–

Note: This table reports the coefficient estimates of the logistic regression model described by Eq. (11) for each Chinese equity sector over the entire sample period. The dependent variable is a dummy variable that takes the value of 1 if the BSADF statistic in t for a given Chinese equity sector is above the 5% critical value, that is, if a period of explosiveness occurs in that sector in t, and 0 otherwise. The explanatory variables are dummy variables constructed in exactly the same way as the dependent variable for each of the remaining ten Chinese equity sectors. As usual, *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

episodes. In fact, the explosive dynamics during these periods seems to be especially pronounced in the Industrials, Materials and Utilities sectors. Furthermore, the similar sectoral pattern of explosiveness suggests potential interactions among episodes of explosivity in different Chinese equity sectors, which will be tested below.

Table 5 presents the results of the co-explosivity analysis in the Chinese equity sectors based on the estimation of the logistic regression model specified in Eq. (11). This model allows quantifying whether explosive episodes in a given sector are significantly associated with explosive episodes in the remaining sectors. Overall, the results reveal that periods of explosive dynamics in any Chinese equity sector are contemporaneously related to explosivity periods in many other sectors, suggesting the presence of co-explosive behavior. For example, the presence of explosiveness in the Industrials and Materials sectors seems to be significantly related to the occurrence of explosiveness in many other sectors, such as Financials, Energy, Health Care, Utilities, and Telecommunication. Instead, Energy and Consumer Staples appear as the sectors whose explosive dynamics is less influenced by the explosive behavior of the remaining sectors. This evidence of co-explosivity at the sectoral level indicates that the explosive dynamics in the Chinese stock market is not generally a sector-specific phenomenon, but rather tends to affect multiple sectors at the same time and, therefore, has important implications in terms of systemic risk for the Chinese stock market.

6. Concluding remarks

The tremendous growth of the Chinese equity market since the mid-2000s coupled with its unique features, such as the prevalence of retail investors, the minor role of foreign investors, the heavy weight of state-owned companies and the significant restrictions on the tradability of shares, have generated a great interest to learn about the periods of irrational exuberance in Chinese stock prices. In this context, this paper extends previous research by examining the presence of explosive dynamics in the Chinese stock market at the sectoral level from January 2005 to December 2022. To that end, the procedure for identification of explosive behavior recently developed by Phillips and Shi (2019), which is capable of detecting both bubbles and market collapses, is implemented together with the new bootstrap technique of Phillips and Shi (2020), which, in turn, deals with both heteroskedasticity and multiplicity issues in recursive inference methods.

The empirical results clearly show various episodes of explosiveness in all Chinese equity sectors, although there is some heterogeneity across sectors as to the number, precise location and length of such episodes. However, two major periods of explosivity affecting simultaneously most Chinese equity sectors are identified and correspond to the widely recognized 2007 Chinese stock bubble and 2015 Chinese stock market crash. Moreover, there seems to be a considerable degree of co-movement of episodes of explosiveness in different sectors, suggesting a high risk of contagion of explosive dynamics among Chinese sectors. The appearance of several episodes of explosivity in a relatively short span of time discloses the strong proclivity of the China's equity market to explosiveness. This outcome can be explained by two main reasons. First, the speculative and short-term trading strategy, based primarily on hearsay, rumors and irrational projections, followed by most Chinese retail investors make them more prone to overconfidence and herd mentality and, given their dominant role in the Chinese stock market, boost the proliferation of explosive dynamics. Second, the early development stage of the Chinese stock market stemming from its fairly recent establishment also favors the emergence of irrational and herd mentality of investors and, hence, the formation of stock market bubbles. In essence, the Chinese equity market is still an emerging capital market subject to frequent and sharp fluctuations compared to more mature and stable stock markets of developed countries.

The recurring roller coaster dynamics of the Chinese stock market at the sectoral level over the last fifteen years indicates that this market is far from being mature and requires additional enhancements by economic authorities. On the one hand, it is crucial to reinforce the financial education of Chinese retail investors to avoid irrational trading and herding effects that exacerbate stock market fluctuations and give rise to episodes of explosivity. It would also be of great interest to foster the development of a potent industry of institutional investors to take advantage of the market stabilizing effect associated with their traditional buy-and-hold strategies. On the other hand, the Chinese regulatory authorities should create an effective bubble early warning, monitoring and response system at the sector level to prevent heightened systemic risk in the stock market associated with contagion of explosiveness across sectors and endangering financial stability. It is also fundamental to implement measures that encourage long-term investment in Chinese equity sectors and favor the transformation of the current speculative stock market into a market oriented towards investment and more correlated with the real economy. These initiatives, via, for example, progressive dividend policies or long-term tax benefits, would increase investors' patience and confidence in companies' long-term value creation, thus reducing the vulnerability of the Chinese equity market to the formation of speculative bubbles, whose subsequent bursting may have severe consequences on the Chinese real economy and social fabric. Lastly, Chinese investors should try to sidestep the prevailing herd mentality and prioritize investment strategies based on the financial health and growth prospects of companies.

CRediT authorship contribution statement

Hui Yang: Data curation, Software, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Román Ferrer:** Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing.

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