5 IDENTIFYING MULTIPLE BUBBLES AND TIME-VARYING CONTAGION EFFECT BETWEEN IRON ORE AND CHINA'S STOCK MARKETS: A NEW RECURSIVE EVOLVING TEST

Shuo YANG[1]*

Abstract

As the rapid expansion of derivatives markets, institutional investors are trading frequently between iron ore and stock markets, and fast capital flows raise the possibility of risk spillover among markets. This paper is the first to study the bilateral risk spillover effect by identifying multiple bubbles and contagion relationship between iron ore and stock markets based on the new recursive evolving test. Three key findings are obtained. First, there are multiple bubbles in both markets, and the formation of bubble is highly associated with market liquidity and investor's expectation. Second, risk spillover relations are time-varying, and there have been a bilateral contagion effect of bubbles among markets during the post-COVID-19 era, reflecting the financialization of iron ore market. Third, the direction of contagion is from iron ore to China's stock market and the reverse direction for second, meaning that the substitution effect has already transformed to linkage effect with the development of iron ore future market. To offset investment risk, investors can add low-correlation assets to construct portfolios, and portfolio diversification strategies must be time-varying.

Keywords: *Multiple bubbles; Risk spillover; Time-varying contagion effect; BSADF; Recursive evolving test*

JEL Classification: *G01, O13, Q31*

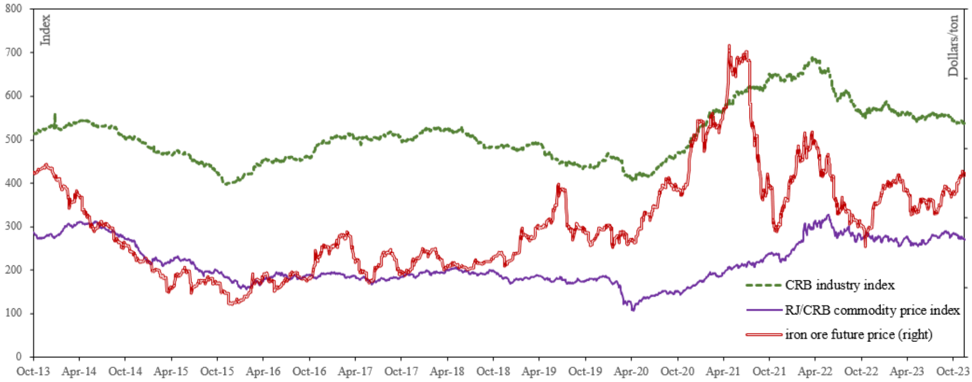
1. Introduction

Iron ore is the second most traded bulk commodity in the world next to crude oil, which is critical for industrial development and economic growth. Due to socio-political unrest and increased uncertainty in recent years, the prices of commodities such as iron ore have witnessed an abnormally fluctuated trend (Kim *et al*., 2023). The declines of the CRB industry index and RJ/CRB commodity price index are alarming 150 points between 2013 and 2015 (Figure 1). Particularly large decline is observed in international iron ore price, which fell from a high of \$138.67/ton to a record low of \$38.15/ton, followed by a period of small fluctuation for about four years. With the COVID-19 epidemic hitting world, the commodity price index has risen sharply and increased by more than 200 points, and the CRB industry index has soared to almost 700

[1] *School of Economics and Management, Tsinghua University, Beijing, 100084, China; Research Center for Technological Innovation, Tsinghua University, Beijing, 100084, China. Corresponding author email: yangshuo@sem.tsinghua.edu.cn*

points. However, the rise of iron ore price is far beyond other commodities, nearly tripling within one year, and iron ore price subsequently falls from 224 to 90 points in six months, which sharply fluctuates and the range has increased. Some scholars have stated recently that the sheer volatility of iron ore price is difficult to interpret with the supply and demand theory, which possesses typical features of a bubble (Etienne, 2017).

Figure 1. International iron ore and commodity price index



Sources: Wind database and Singapore Exchange.

A large quantity of iron ore is imported by sea to satisfy the increasingly strong demand for resources because of China's rapid industrialization and urbanization (Chen and Yang, 2022; Radetzki *et al*., 2008). According to the Wind Database, China's iron ore consumption has increased from 0.3 to 1.4 billion tons during the period 2000-2023. China accounts for more than half of global consumption annually after 2006, which led to a degree of dependence on imports over 80 percent in recent years. In this context, international iron ore price shifts have significant impacts not only on China's inflation (Chen and Yang, 2021) and economic growth (Hoang and Nguyen, 2018) but also on financial market (Gutierrez and Vianna, 2018; Gomwe and Li, 2019). For example, if the price of iron ore rises sharply, the increased cost will contribute to a rapid decline in investment and economic output, which will have a detrimental impact on China's stock market. Nevertheless, there is the positive impacts of soaring resource prices on stock market due to risk spillover effect and investors' sentiments (Zhao *et al*., 2020; Li and Wei, 2018; Ben and Azrak, 2023; Long *et al*., 2024). In addition to the ambiguous impacts of iron ore on the stock market, economic development and stock market performance in turn can affect iron ore price because of the massive import in China.

Considering the distinct bubble features of iron ore price and the complex relationship among markets, this is the first study on the risk contagion between iron ore and the stock market from the new perspective, i.e., bubbles contagion. Specifically, this paper focused on the following research questions. Do multiple bubbles exist in both international iron ore and China's stock markets? What is the contagion relationship of multiple bubbles between markets? What is the direction of risk spillover in iron ore and stock markets? Answering these questions is critical to identifying financialization of iron ore market and the close coupling relationship between iron ore and stock markets.

This paper adopts the GSADF and BSADF methods to identify the bubble episodes in China's stock and international iron ore markets from October 18, 2013 to December 1, 2023, and multiple bubbles are detected in both iron ore and stock prices. Furthermore, A new Granger causality test is adopted to explore the risk spillover relations across two markets. The results show that there are three episodes of bubble contagion during the sample period, and the last one confirms the existence of bilateral risk spillover effect during the post-COVID-19 era.

The primary work and contributions in this research article are as follows. On the one hand, previous research mainly focused on spillover effect from return and volatility perspectives, few on the spillover effect of bubbles across markets. Based on the new perspective of bubble contagion, this study examines the risk spillover effect between iron ore and the China's stock markets in both positive and negative directions. On the other hand, the relationship between iron ore and stock markets exhibits inherent instability under current geopolitical and macroeconomic uncertainties. This study employs the recursive evolving Granger causality test to quantify time-varying risk transmission mechanisms and circumvent the identification constraints inherent in fixed-parameter models.

The subsequent sections of the article are arranged as follows: Section 2 presents a review of the existing literature regarding the causes of iron ore bubble and relations between iron ore and stock markets. Next section introduces the GSADF, BSADF methods, and the dynamic Granger causality tests. The research data is displayed in Section 4, and Section 5 analyses the empirical findings on bubbles detection and bubble contagion. The robustness check is presented in Section 5, and the last one describes the conclusions and policy recommendations.

2. Literature review

High volatility in iron ore and stock prices has attracted intensive attentions from both industry and academia in recent years. On the one hand, existing studies often assume that the drastic fluctuations in iron ore price are accompanied by the occurrence of bubbles. For instance, Su *et al*. (2017) explore the existence of multiple bubbles and the reasons for bubbles over the period 1980-2016, and their results show that four bubbles appear in fluctuating periods. The first three bubbles are primarily attributed to the demand-supply imbalance and the change in pricing regime, while the last one is caused by the adverse effects of global financial crisis (GFC). After the onset of GFC, a large number of funds flowed into the commodity markets, including iron ore, which drives up iron ore price and results in the bubble bursting (Creti *et al*., 2013; Eichengreen, 2013; Gharib *et al*., 2021; Zhao *et al*., 2015). Moreover, some scholars argue that asset price bubble often correlates closely with irrational trading behavior. A Reuters article, for example, believes that soaring iron ore price reveals irrational exuberance triggered by investors' sentiments2. Etienne (2017) confirms the existence of multiple bubbles in iron ore market, and the biggest bubble appeared in the period of low liquidity.

On the other hand, many scholars detect multiple bubbles in the Chinese financial market. Meng *et al*. (2020) investigate the possibility of price bubbles in China's stock market, and there are two bubble periods: from April 2005 to October 2007 and June 2015 to November 2015. Shu and Zhu (2020) readily detect multiple bubbles of China's stock market from early 2014 to mid-2015, and they further identify three positive bubbles and four negative bubbles in the CSI 300 index during the period 2005-2018. Li *et al*. (2021) apply the BIADF and the BSADF tests to identify the bubble initiation and termination dates, and two typical bubbles (the well-known 2007/2008 GFC and 2015 stock market disaster) are successfully identified.

Previous studies pay more attention to multiple bubbles in iron ore and China's stock markets, respectively. However, they fail to link up the abnormal behaviors in these markets. Consequently, this study intends to fulfill the gap by analyzing the correlation between market bubbles. Recently, more attention has been paid to the linkage between iron ore and stock markets, and it is commonly accepted that the high correlations are between the two markets. For example, Burdekin and Tao (2021) analyse the correlation between iron ore and China's stock indices

[2] *http://www.reuters.com/article/us-ironore-supply-ahome-analysis-idUSKCN0YI18U, accessed on 30 June 2016.*

across both low- and high-volatility regimes, finding a statistically significant relationship exclusively during low volatility periods. Ma and Wang (2021) explore the time-varying price spillover effect between iron ore and China's steel stock prices and find a significant spillover effect of iron ore on steel stock. Asadi *et al*. (2023) attempt to shed light on the volatility connectedness among iron ore and stock markets in Australia. Asadi *et al*. (2023) further examine temporal volatility spillover among iron ore and stock markets in China and the United States under bearish and bullish conditions.

Most of these previous studies focus on the general link between iron ore and stock markets, such as return link and volatility spillover. Nevertheless, little research has attempted to investigate the contagion effect among markets from the perspective of bubble contagion. In this context, this paper first measures multiple bubbles in iron ore and China's stock markets using the GSADF test, then identifies the initiation and termination of bubbles based on the backward SADF test, and finally investigates the time-varying contagion effect of bubbles.

3. Methodology

3.1. Bubble Detection

A bubble is commonly defined as the nominal asset price deviates from its fundamental value, and then result in a rapid retraction of the market price. The earliest study identifying asset price bubbles based on fundamental value can be traced back to the asset pricing model (Lucas, 1978). Following this, there are plenty of empirical models for detecting asset price bubbles. Among them, the most representative one is the rational bubble model (Diba and Grossman, 1988; Hamilton and Whiteman, 1985), which is premised on efficient markets theory and rational expectations with a solid theoretical foundation. Therefore, the research of this article is based on this model.

The asset pricing model begins with the following equation (Gürkaynak, 2008):

$$P_t = \sum_{i=0}^{\infty}(\frac{1}{1+r_f})^i E_t(\delta_{t+i} + U_{t+i}) + B_t \tag{1}$$

Where P_t is the price for period t, r_f stands for risk-free interest rate, E_t represents equation, δ_{t+1} indicates earning at period $t+1$, and U_{t+1} denotes invisible component of market. In general, $P_t^f = \sum_{i=0}^{\infty}(\frac{1}{1+r_f})^i E_t(\delta_{t+i} + U_{t+i})$ represents fundamental value of asset, while B_t indicates bubble component.

$$B_t = (1 + r_f)^{-1} E_t(B_{t+1}) \tag{2}$$

Moreover, equation (1) can be written in the general form:

$$P_t = P_t^f + B_t \tag{3}$$

Equation (3) represents that asset price is composed of the fundamental value and bubble component. When $B_t = 0$, the asset price exists no bubble, which is determined by its fundamental value. If B_t is not equal to zero, it reflects that bubbles exist in the asset price.

Hamilton and Whiteman (1985) examine bubble existence based on the unit root test method. Diba and Grossman (1988) state that besides the unit root test, the cointegrating relationship between stock price and dividend is required to validate, and no bubble exists during the sample period if stock price is cointegrated with dividends and they have the same order. Nevertheless, Evans (1991) points out that the above-mentioned methods tests have little power to identify explosive bubbles. As a result, the supremum Dickey-Fuller (DF) test is proposed to address this question.

The sup ADF test uses recursive sequences of standard ADF tests based on a forward expanding sample and takes the sup value of the statistics sequence. The SADF can be defined as the following equation:

$$SADF(r_0) = sup_{r_2 \in (r_0, 1)} \left\{ ADF_0^{r_2} \right\} \tag{4}$$

The window size r_w ranges between r_0 and 1, where r_0 and 1 stand for the minimum and maximum window length, respectively. The beginning point r_1 is fixed at starting point 0 and the ending point r_2 equals to r_w and varies between r_0 and 1, and the ADF statistic from zero to the ending point is denoted by $ADF_0^{r_2}$.

The SADF test is effective when there exists a unique bubble during the sample period, whereas most datasets are far more than one bubble. To overcome this problem with failed detection of multiple bubbles, the generalized sup ADF test has been developed (Phillips *et al.*, 2015a). Besides the r_2 is not fixed, the starting point r_1 is permitted to vary from zero to $1 - r_w$. As the GSADF test obtains more information and allows greater flexibility of window, it significantly outperforms the SADF test when there is more than one bubble during the study period.

$$GSADF(r_0) = sup_{r_2 \in [r_0, 1], r_1 \in [0, 1 - r_w]} \left\{ ADF_{r_1}^{r_2} \right\} \tag{5}$$

When an intercept is included in this model and the null hypothesis assumes random walk, the limit distribution of the generalized sup ADF test statistic is defined as below:

$$sup_{r_2 \in (r_0, 1), r_1 \epsilon (0, r_2 - r_0)} \left\{ \frac{\frac{1}{2} r_w [W(r_2)^2 - W(r_1)^2 - r_w] - \int_{r_2}^{r_1} W(r) d_r [W(r_2) - W(r_1)]}{r_w^{\frac{1}{2}} \left\{ r_w \int_{r_2}^{r_1} W(r)^2 d_r - [\int_{r_2}^{r_1} W(r) d_r]^2 \right\}^{\frac{1}{2}}} \right\} \tag{6}$$

Where W denotes the Wiener process and r_w equals $r_2 - r_1$. Comparing the GSADF statistics to its critical values could bring the relevant result of whether there are multiple bubbles or not. One limitation of the test is that it fails to identify the starting and ending time points of asset bubbles. To address this issue, Phillips *et al*. (2015b) further develop the BSADF test to accurately determine the dates of bubbles.

The r_2 is fixed, and the beginning point r_1 is varying between zero and $r_2 - r_0$. The unit root test sequence is represented as $\left\{ BADF_{r_1}^{r_2} \right\}_{r_1 \in [0, r_2 - r_1]}$, and the detailed backward SADF statistic is presented below:

$$BSADF_{r_2}(r_0) = sup_{r_1 \in [0, r_2 - r_0]} \left\{ BADF_{r_1}^{r_2} \right\} \tag{7}$$

The r_2 falls between r_0 and 1, and a set of the BSADF statistics can be obtained. When the BSADF statistic exceeds the given critical value for the first time, the first bubble appears, and the bubble bursts when the statistic is below the cut-off value, followed by the second bubble, and so forth.

3.2. Time-varying Granger causality test

Granger causality test is mainly used to assess the links among commodities prices and stock index in previous studies, and this method has become popular primarily because it is not specific to structural models but is dependent on the variable's nature (Balcilar *et al.*, 2018). However, the contagion effect between stock and commodities markets may be time-varying due to multiple factors such as economic policy uncertainty and geopolitical risks, so statistical methods based on the assumption of constant parameters (for example, the Granger causality) may lead to inaccurate results. In fact, three main tests are applied to explore the time-varying causal links among variables in the existing literature. One is a forward expanding test (Thoma, 1994), and the second one is a rolling test (Swanson, 1998), and the third is the recursive rolling test (Shi *et al*. 2018).

Shi *et al.* (2018) compare the accuracy in causality detection rates of these three tests and reveal that recursive rolling method produces the best results in finite samples, followed by the rolling window approach. Consequently, this paper primarily employs the recursive rolling method to explore the dynamic contagion effect, and both previous tests are also considered simultaneously to evaluate these three methods.

A bootstrap method is proposed to tackle the multiplicity problem, which is based on the bivariate VAR (1), and this process can be extended to a high-dimensional system. The detailed procedure of the bootstrap algorithm is implemented as follows.

In the first step, the bivariate VAR (1) model is estimated under the null hypothesis of no causal link between y_{1t} (iron ore price) and y_{2t} (CSI300 index), and the resultant equation is shown below:

$$\begin{bmatrix} y_{1t}^b \\ y_{2t}^b \end{bmatrix} = \begin{bmatrix} \emptyset_{11} & 0 \\ \emptyset_{12} & \emptyset_{22} \end{bmatrix} \begin{bmatrix} y_{1t-1}^b \\ y_{2t-1}^b \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t}^b \\ \varepsilon_{2t}^b \end{bmatrix} \tag{8}$$

where ε_{1t}^b and ε_{2t}^b are the estimated residuals of the VAR (1) model.

In the second step, the statistic sequences are calculated using the forward recursive, rolling and recursive rolling tests respectively. The statistic sequences for these three tests are reported as follows:

The forward recursive test:

$$M_{1,t}^b = \max_{t \in [\tau 0, \tau_0 + \tau_b - 1]} (W_{1,t}^b) \tag{9}$$

The detection method is based on the rolling procedure :

$$M_{t-\tau_0+1,t}^b = \max_{t \in [\tau_0, \tau_0 + \tau_b - 1]} (W_{t-\tau_0+1,t}^b) \tag{10}$$

The recursive rolling test:

$$SM_t^b(\tau_0) = \max_{t \in [\tau_0, \tau_0 + \tau_b - 1]} SM_t^b(\tau_0) \tag{11}$$

In the third step, the above two steps are repeated for $b = 1, \dots, 499$.

In the final step, the critical values of three main methods are the 95% percentiles of the $\{M_{1,t}^b\}_{b=1}^B$, $\{M_{t-\tau_0+1,t}^b\}_{b=1}^B$ and $\{SM_t^b(\tau_0)\}_{b=1}^B$ sequences respectively.

4. Data

To comprehensively identify the multiple bubbles in international iron ore and stock markets, and investigate the bubble contagion effect between these two markets. The analysis presented in this paper is based on iron ore price and China's stock index from October 18, 2013 to December 1, 2023, totaling 2395 daily closing data. The Singapore Exchange (SGX) initiated the first iron ore futures trading based on imported iron ore price3 in April 2013. In October of the same year, the iron ore futures trading has been initiated in the Dalian Commodity Exchange (DCE) of China. The SGX is currently the trading center of dollar settled for iron ore, while the DCE has become the most significant trading center for iron ore derivatives (Etienne, 2016). In light of this, the iron ore futures closing price in the SGX (SFP) can be used as a proxy for international iron ore price, and the future price in DCE (DFP) is employed as another indicator to ensure stable and consistent results. Moreover, China's stock market is largely comprised of the Shanghai and Shenzhen Stock Exchange. The CSI300 index is jointly issued by these two exchanges in 2005, and this index reflects the performance of 300 strong liquid stocks. This paper adopts the Shanghai Securities Composite Index (SHCOMP) as another proxy variable for China's stock

[3] *The closest proxy available for iron ore price is the 62% FE spot CFR Tianjin port.*

market price. The data are obtained from the Wind database.

Table 1. Descriptive statistics of study variables

Variable	Mean	Std. dev.	Kurtosis	Skewness	Min	Max	JB	ADF
SFP	95.94	36.55	0.96	0.97	38.15	223.94	793.65a	I (1)
CSI300	3777.62	773.61	-0.10	-0.10	2086.97	5807.72	961.26a	I (1)
DFP	656.20	204.75	-0.27	0.50	284.00	1337	1162.91a	I (1)
SHCOMP	3095.13	464.05	2.08	-0.04	1993.45	5166.35	84.21	I (1)

Notes: I (1) denotes the first-order difference stationary, and a represents that the null hypothesis of normal distribution is rejected at the 1% significance level.

The descriptive statistics of study variables are presented in Table 1. The skewness suggests that each variable is skewed positively, and the kurtosis is far less than 3, indicating that these three variables are platykurtic. The Jarque-Bera tests reject the null hypothesis at the 1% level, meaning that each variable obeys the non-normal distribution. Moreover, the standard deviations of the CSI300, DFP and SHCOMP are large, which implies that there may be bubbles in iron ore and China's stock markets during the sample period. The ADF test is applied to assess the stability of time series studied, and the result indicates the first-order difference stationary, which demonstrates a cointegration relationship among iron ore and stock prices. To meet modeling needs and remove seasonal factors, this paper adopts the first-differencing of log time series according to the recent literature (Gharib *et al*., 2021). Next, this paper will empirically test the multiple bubbles of iron ore and stock markets over the period 2013-2023, and further investigate the bubble contagion effect between these markets.

5. Empirical results

5.1 Bubble test

According to the efficient market hypothesis, the asset price fully reflects the historical information and obeys a random walk (Fama, 1970). Summers (1986) argues that asset price reflects its fundamental value when this market is weak-form efficient. Based on this, the efficient market hypothesis has not only been widely concerned by numerous scholars but has also been a solid theoretical basis of asset pricing models and bubble detection tests. For instance, the unit root test is one of the earliest models for bubble detection based on the premise of market efficiency. If the null hypothesis of no bubble in asset price is rejected, there exists at least one bubble in this market. However, the power of the unit root test is too weak to accurately identify market bubbles (Evans, 1991), so Phillips *et al*. (2011) propose the Sup ADF test to address this. However, the SADF test fails when there is more than one bubble in study period. To improve the power for bubble detection, the Sup ADF test is extended to the General Sup ADF method by Phillips *et al*. (2015a), which can accurately identify multiple bubbles. They also present the Backward SADF test to determine the start and end date of bubble episodes in each market.

This paper adopts these two tests to identify the multiple bubbles in the iron ore and Chinese stock markets. Following the suggestion for the smallest window size given in Phillips *et al*. (2015), this paper sets $r_0 = 0.01 + 1.8/\sqrt{2395}$, and the fixed lag order k is set equal to zero. Table 2 shows the results for bubble detection by employing the SADF and GSADF tests. The SADF and GSADF tests reveal that the null hypothesis is rejected at the 5% significance level for each of the series, indicating that there is at least one bubble in both the iron ore and stock markets over the study period.

Table 2. Results of price bubble tests

Variable	SADF test	GSADF test
SFP	1.672**	4.149***
CSI300	4.624***	5.758***
1% critical value	2.141	2.951
5% critical value	1.565	2.511
10% critical value	1.294	2.279

*Notes: *** and ** denote significance at the 1% and 5% levels, respectively.*

The GSADF and BSADF tests are employed to identify multiple bubbles and the bubble dates in each series. Figure 2 and Table 3 show the results of bubble tests and date-stamping in iron ore and stock markets, and study results reveal that there exist multiple bubbles in each series. During the sample period, there are six bubbles in Chinese stock market, which occur centrally in 2014, 2019 and early 2021, and each financial bubble initiates with a parabolic surge in equity valuations (He *et al*., 2024).

China’s stock market has reached a new period of rapid development since the end of 2014, and the CSI300 index experienced a rapid rise for about eight months and hit a record high of 5353 points on June 8, 2015 in a 7-year period. The booming stock market has drawn significant attention from academia, and scholars generally believe that bubbles may exist during this period. The detection result of this paper confirms the existence of market bubbles between November 2014 and June 2015, which is consistent with relevant work conducted by Li *et al.* (2021). This bubble occurs at a time when China’s economy and the real estate market are remarkably cooling and gets disconnected from realities of profitability and economic activity, which is primarily the consequence of strong leverage. Investment behavior among retail Chinese investors along with the herding effect drives up China’s stock index (Sornette *et al*., 2015). Consequently, high market liquidity provided by considerable financial investment and the herding effect is the leading cause of stock price bubble in 2014. Nevertheless, stock selling triggered by the subsequent de-leveraging is a major cause of plummeting stock price, and the first bubble bursts in the middle of 2015 (Bian *et al*., 2018). Meng *et al*. (2020) empirically confirm that the CSI300 index jumped abnormally from June 2015 to November 2015, and China's stock market is more volatile than those of mature international markets, indicating that China's stock market is not yet mature.

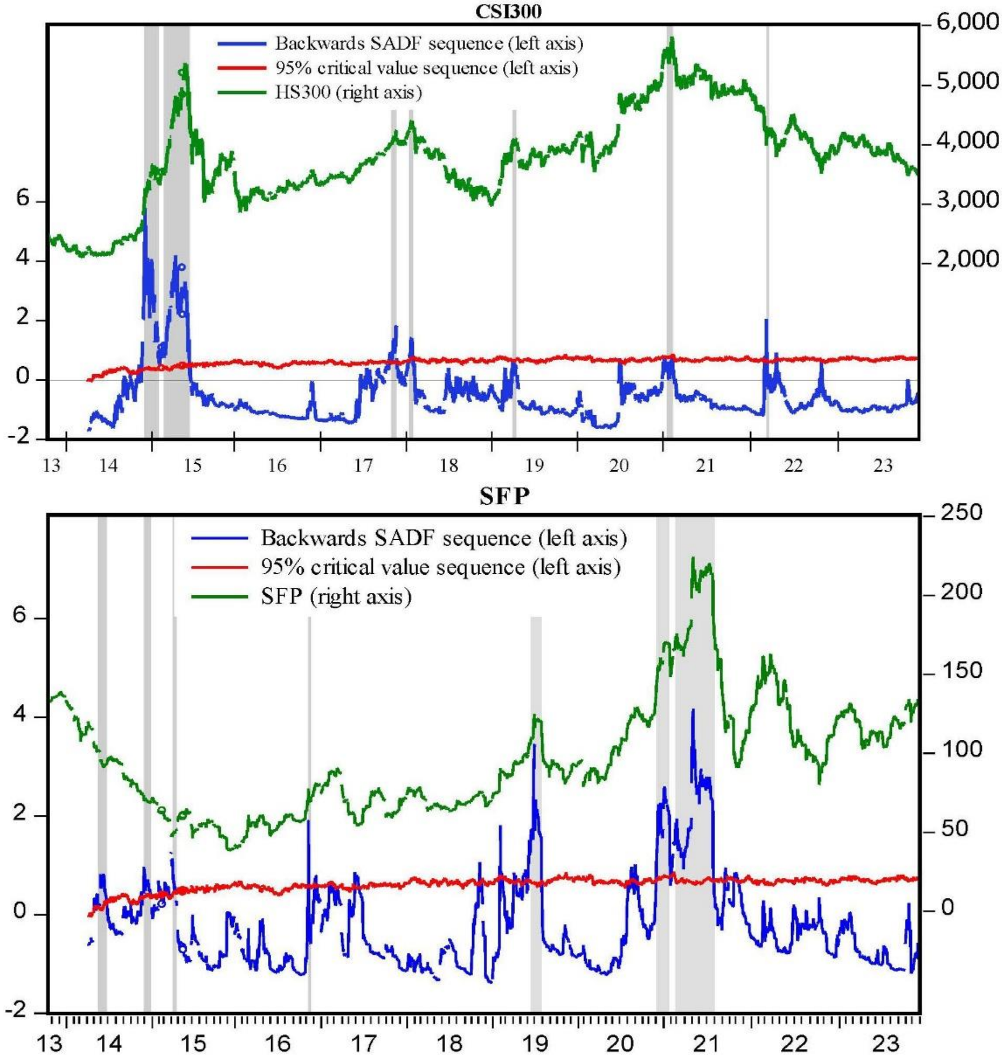
China's stock market has rebounded markedly and entered a brief period of rapid growth since early 2019, and the CSI300 index soared from less than 3000 points to 4120 points, with a nearly 40% rising in a three-month period. The empirical result reveals the existence of multiple bubbles, and this bubble appeared in February 2019 and lasted 53 days, which is primarily attributed to the influx of substantial long-term funds. To ensure stable and prosperous capital market, the China Securities Regulatory Commission (CSRC) has successively revised securities investment regulations to encourage long-term capital to enter the equity market. In addition, The CSRC also revised and integrated the Provisional Measures on Administration of Domestic Securities Investment of Qualified Foreign Institutional Investors (QFII) and the Measures for Pilot Projects for Securities Investment in China by RMB Qualified Foreign Institutional Investors (RQFII), and the quota limit for foreign institutional investors to invest in China's financial market has been lifted. In light of this, a huge amount of money brought liquidity to China's stock market, which drove up the stock price and finally resulted in a bubble.

The latest bubble was observed from January 2021 and burst in February 2021, and the reason for the occurrence of this bubble may be abundant liquidity and economic upturn. The CSI300 index has begun to rebound after it bottomed on March 23, 2020, which is highly related to market liquidity. In fact, to cope with the impact of COVID-19, the People's Bank of China (PBOC) has improved market liquidity by expanding its balance sheets since April 2020, which has led to sustained price increases. However, the fast-growing market is usually accompanied by bubble creation. Thus, abundant liquidity is an important cause of this bubble in China's stock market. Furthermore, the economic upturn is another cause of the formation of bubbles. There is a strong positive association between economic development and stock price movement as stock market is a crucial barometer of the economies (Younis *et al*., 2020). According to the IMF prediction, China's GDP growth rate would reach 8.1% in 2021, and the improving economy bolsters investors' confidence. As a consequence, the economic growth expectation partly drives up China's stock prices and forms a bubble. The subsequent collapse of the China's stock market bubble can be attributed to structural bubbles in specific industries and sectors, whose collapse generated ripple effects that propagated systemic risks across the entire market. This contagion mechanism is substantiated by Ji and Zhang (2024) empirical analysis, which identified the liquor sector bubble's rupture in the first quarter of 2021 as the primary catalyst for the subsequent market-wide risk escalation.

The lower half of Figure 2 shows that there are seven bubble episodes in iron ore price, which occur centrally in 2014, 2019, 2020 and the early of 2021. This paper detects three short, negatively explosive episodes during 2014-2015, and there are also four positive explosive episodes in 2016-2021 due to the price surge. First, the two bubble episodes occurred in 2014: from May 19 to June 20, 2014, and from November 20 to December 18, 2014, corresponding to the periods of low liquidity. The empirical findings supported previous research indicating that the existence of a bubble is strongly linked to market liquidity. For instance, Etienne (2017) argues that low liquidity is a crucial factor in bubble occurrences in 2014. As a market with low liquidity is generally fragile, its price may be easily influenced by exogenous shocks or pricing errors caused by investor sentiment, resulting in a bubble (Jarrow *et al*., 2012). Moreover, Wårell (2018) points out that a growing production capacity is brought to international iron ore market in 2014, but market demand for iron ore is significantly weak because of slowing economic growth in China, which results in the growth of supply has exceeded that of market demand. Given this background, the iron ore price began to fall dramatically and the over 10-year long commodity boom was punctuated in 2014. Consequently, low liquidity and oversupply result in a rapid decline in international iron ore price, and the iron ore price deviates from "fundamental value" to form a bubble.

The second important bubble period appeared in November 2016 and burst at the end of November 2016, which persisted for 14 days. Figure 2 displays that iron ore price shows a rising trend and jumps from \$62/ton to \$80/ton, with an increase of over 29%. One possible reason for bubble occurrences is that the domestic huge demand for iron ore drives up its price significantly and leads to a bubble. China's real estate market experienced rapid growth in 2016, and the construction starts were 1.67 billion square meters, a year-on-year increase of 8.1%, which resulted in huge demand for steel and iron ore. In fact, China's iron ore imports exceeded one billion tons for the first time in 2016, and the soaring demand contributed to increased iron ore price and formed a bubble. On the other hand, according to Etienne (2017), the occurrence of the bubble was mainly triggered by the animal spirits of noisy traders in 2016. A vast array of iron ore future contracts is traded on SGX, with record-high levels achieved in 2016. As a result, bubble formation was induced by the increasing demand for iron ore and investor sentiment.

Figure 2. Bubble periods in CSI300 and SFP



Notes: the green line is the CSI300 index and SFP respectively, and the shaded areas are the bubble periods.

Another market bubble began in June 11, 2019 and persisted for 51 days. The iron ore price entered a period of rapid growth at the start of 2019, with an increase of up to 74.6% within half a year. There are three possible reasons for this bubble. One possible reason is that almost 6% of the global iron ore production was subsequently suspended due to a serious mine accident in Brazil, resulting in the tight iron ore supply condition. The second reason is the increasing demand. With the arrival of the no-heating season, the relaxing of production-limiting policies led to an increase in the production of hot metal and demand for iron ore. The last one may be attributed to the increased freight rate. Because of the much lower value-to-weight ratio of iron ore, the iron ore trade is mostly realized through transporting by sea, so freight rate is an important component of the price (Ma *et al.*, 2013). Chen *et al*. (2023) point out that the sea freight constituted over 50% of the Free on Board (FOB) price of iron ore during peak shipping cost periods, so sea freight rates have exerted a substantial influence on iron ore price. However, the impact of hurricane in 2019 directly pushed up sea freight rates, which further led to a surge in iron ore prices. Therefore, the increased demand-supply gap and freight rate drive iron ore price from fundamental value and form the price bubble. Nonetheless, the demand gap has been gradually met by the increasing supply of iron ore since July 2019, which leads to the decline in price, resulting in the bubble bursting quickly.

The last two bubbles with long-term duration started in late 2020 and early 2021. The primary reason for these bubbles is the ever-growing demand. According to the data released by the General Administration of Customs of China, China imported 11.7 billion tons of iron ore in 2020 with a yearly rate of about 10%. Jowitt (2020) holds the view that the COVID-19 crisis is analogous to World War II, with the crisis followed by rapid economic development and increased steel consumption related to reconstruction globally, and COVID-19 delayed investment but increased infrastructure investment, which will cause great iron ore demand and large increases in its prices. Notably, the episodes of the bubbles in iron ore and stock markets almost perfectly overlap in 2021, indicating that there may be a contagion effect among these markets during this study.

Table 3. The specific dates of bubbles in CSI300 and SFP

CSI300	Collapse	Duration	SFP	Collapse	Duration
2014.11.24	2015.1.29	67	2014.5.19	2014.6.20	32
2015.3.2	2015.6.23	142	2014.11.20	2014.12.18	29
2017.11.7	2017.11.24	18	2015.4.1	2015.4.10	10
2018.1.19	2018.1.29	11	2016.11.10	2016.11.23	14
2019.2.25	2019.4.18	53	2019.6.11	2019.7.31	51
2021.1.7	2021.2.5	30	2020.12.4	2021.1.28	51
2022.3.12	2022.3.17	6	2021.2.9	2021.7.27	161

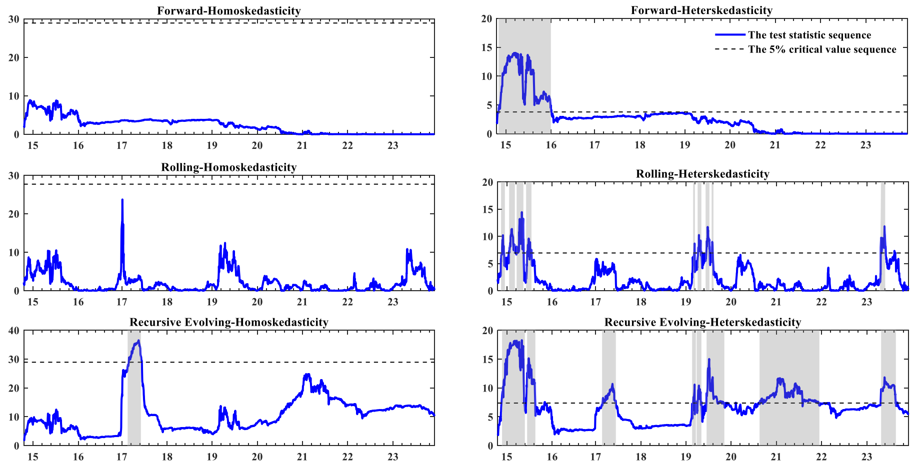
Notes: there are 2395 observations in this paper (i.e., $T = 2395$). Following to Phillips et al. (2011), this paper only considers the bubble if the duration is greater than 7 days ($log(T)$).

5.2. Contagion effect of multiple bubbles

Figure 2 shows that the CSI300 and SFP have risen sharply in the first half of 2019 and the last year of study, and bubble episodes are nearly overlapping. The question thus arises whether the bubbles in these two markets are closely related. To answer this question, this paper will investigate the contagion relationship between iron ore and China's stock markets. In line with the recent literature (Zhao *et al*., 2020), two conditions need to be met for bubble contagion. On the one hand, the bubble episodes nearly overlap among the two markets. On the other hand, there is a causal relation among two markets applied by the Granger tests. According to the results of date-stamping of bubbles in Table 3, bubble contagions between these markets may occur during the following periods: from November 2014 to June 2015; from February to July 2019; and the last from December 2020 to July 2021.

This paper next employs three tests of time-varying Granger causality to explore the causal relationships among iron ore and stock markets, with the assumption of the residual error term (homoskedasticity or heteroskedasticity) for the VAR (1). When the Wald test statistics exceed the 5% critical value, the null hypothesis of no direct causal link is rejected. The empirical size of this paper is 5% and is limited in a two-year period, and the minimum window size (f_0) is set as 0.1, with 240 observations.

Figure 3. Tests for Granger causality from SFP to CSI300



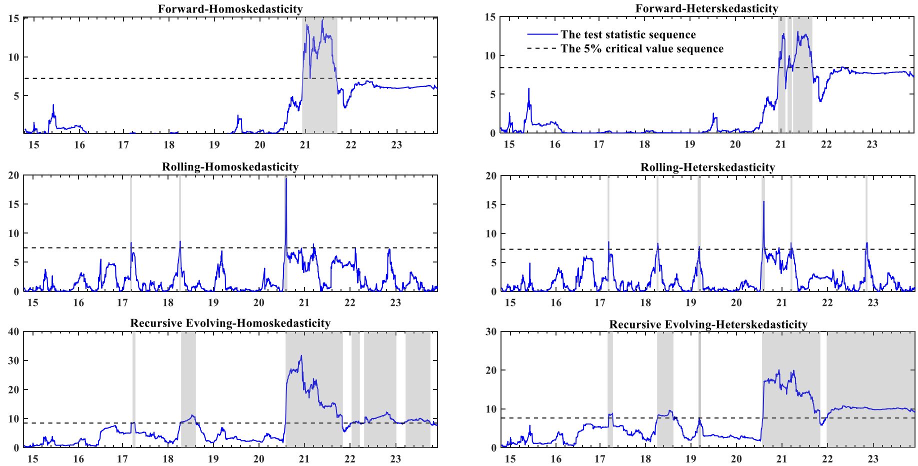
Notes: The blue lines are the test statistic sequence; the dotted lines denote the 5% critical value sequence, and the shaded areas are causal periods; The arrow indicates the occurrence date of bubble.

The results demonstrate that the recursive rolling test finds more episodes of causality running during the entire sample period under the homoskedasticity or heteroskedasticity condition, and the evidence of causality based on the heteroskedastic-consistent tests is stronger (Figure 3). First, the heteroskedasticity-consistent recursive algorithm finds an episode of causality from iron ore to stock market in 2014, starting in November 2014 and ending in June 2015, and Table 3 shows that the bubble of iron ore price occurred on November 20, 2014, and the bubble in China's stock started on November 24, which can meet the above two conditions of bubble contagion at the same time. Consequently, these results indicate that the bubble was observed on November 20, 2014, which spread to China's stock market after four days (i.e., November 24). Second, there may be another period of bubble contagion from iron ore to stock market: from February to July 2019, because bubbles occurred in these two markets, and the causal effect is found over this period. However, the iron ore price bubble started significantly later than in China's stock market. The two conditions of bubble contagion cannot be satisfied simultaneously, so there is no bubble contagion effect from iron ore market to stock market in 2019. Moreover, the last period of bubble contagion is likely to cover the time from December 2020 to July 2021. There is the existence of causality from iron ore to stock market. As a matter of fact, the iron ore bubble appeared in December 2020 and earlier than that in China's stock market (January 2021), which could meet the above conditions at the same time, indicating a bubble contagion. Hence, the contagion effect of bubbles from iron ore to stock market has been identified during the periods of 2014-2015 and 2020-2021.

Figure 4 shows the Granger causality from stock to iron ore market. The results do not vary much under the assumption of conditional homoskedasticity or heteroskedasticity, but the recursive rolling test finds more episodes of causality and offers better performance than the forward recursive and rolling tests. As mentioned previously, the bubble contagion effect may occur during these periods: from November 2014 to June 2015; from February to July 2019; and the last from December 2020 to July 2021, and this paper will analyze the possible episode of bubble contagion one by one.

First, the test statistics are below their critical values during the 2014-2015 period, which indicates that the null hypothesis of no inverted causality from stock market to iron ore market could not be rejected, so these two conditions of bubble contagion are not met simultaneously. Second, this paper detects a short episode of causality from stock to iron ore from February to July 2019, and the stock bubble appears in February 2019 and much earlier than that in iron ore market (June 2019), revealing the bubble contagion effect in early 2019. Last, there is an episode of causality from December 2020 to July 2021. The stock bubble begins in January 2021, which is earlier than the time of the iron ore bubble (February 2021), and the two conditions of bubble contagion are satisfied. As a consequence, there are two episodes of bubble contagion from stock to iron ore market: from February 25, 2019 to July 31, 2019; and from January 7, 2021 to July 27, 2021.

Figure 4. Tests for Granger causality from CSI300 to SFP



Notes: The blue lines are the test statistic sequence; the dotted lines denote the 5% critical value sequence, and the shaded areas are causal periods; The arrow indicates the occurrence date of bubble.

Overall, there are three episodes of bubble contagion in iron ore and stock markets during the whole study period. The directions of three bubble contagion are from iron ore to stock market for the 2014-2015 bubble, from stock to iron ore for the 2019 bubble, and a bilateral for the 2020-2021 bubble (from iron ore to stock market from December 2020 to January 2021; from stock to iron ore market from January to February 2021), respectively.

The first bubble contagion from iron ore to China's stock market reveals that China's economic slowdown in 2014 and a decline in infrastructure investment caused the demand for bulk commodities like iron ore to fall. Meanwhile, a sizable new capacity was introduced into the iron ore industry. The oversupply of iron ore causes its price to fall dramatically and forms a negative bubble (Wårell, 2018). Iron ore is the most significant raw material in steel production, accounting for up to 40-50% of the cost. Therefore, the falling iron ore price is bound to get higher profits for steel and downstream companies, which pushes up industry stock prices and further creates a stock bubble. This result is similar to the finding of Ji and Zhang (2024), who demonstrate that the overall stock market bubble is triggered by the industry-specific bubble. In addition, there is the substitution effect among commodity and the stock markets (Gorton and Rouwenhorst, 2006; Erb and Harvey, 2006). Gannon (2005) points out that both commodity and stock markets have investment opportunities. When the investment risk of the commodity market is high, the funds flow from the commodity market into stock market to avoid risks. Consequently, the massive funds flowed out of iron ore market to avoid risk due to the negative iron ore bubble, and one of the destinations for hedge funds was China's stock market. Large cash flows pushed up the Chinese stock index and resulted in a positive bubble in 2014.

The second bubble contagion from stock market to iron ore market occurred in early 2019. The securities investment regulations revised by the CSRC provided great convenience to the influx of money, which improved market liquidity and drove up the stock price. Specifically, the CSI300 index increased by more than 1000 points from January to April 2019, with a bubble occurrence during this period. In recent years, the strong associations are revealed between stock and international commodity markets such as iron ore and gold, as commodity markets have attracted a lot of attention from investors, who usually focus on portfolio allocation between commodities and other assets such as stocks and bonds (Tang and Xiong, 2012). The large investment flow triggered by cross-market transactions precipitated the process of financialization of commodity markets, making stock volatility a key cause of commodity volatility. Therefore, the 2019 bubble started in stock market and then spread to iron ore market. Moreover, the above two results of bubble contagion indicate that the substitution effect in 2014 has been changed into a linkage effect in 2019 between stock and iron ore markets.

There is a bi-directional contagion effect of bubbles between iron ore and China's stock markets over the 2020-2021 period. Chinese steel industry evolved slowly in early 2020 because of the COVID-19 outbreak. After the resumption of work and production, the surging demand for iron ore drove up its price, which increased dramatically from April to December 2020, rising from $81/ton to reach the high point of $160/ton, and a bubble appeared in December 2020. The iron ore bubble subsequently migrated to China's stock market in January 2021. A possible reason for the bubble contagion from iron ore to stock market is that iron ore market volatility can the trigger plate linkage effect of stock market. The blocks are divided according to industry, location and concept in Chinese stock market, and stocks in the same block are changing synchronically over the same period, with strong correlations within the block (Zhen *et al*., 2017). The plate linkage effect triggered by the increased iron ore price will further affect the whole stock market and result in a stock bubble consequently. Furthermore, the reason for the bubble contagion effect from stock to iron ore market in 2021 is similar to the bubble contagion in 2019. The stock volatility becomes the main cause of commodity volatility due to the frequent flow of funds between these markets, resulting in an inverted bubble contagion in early 2021. Therefore, this paper finds remarkable new evidence for the bi-directional contagion effect among iron ore and China's stock markets, revealing the financialization of iron ore market.

6. Robustness check

To confirm the accuracy and reliability of findings, this paper conducts three robustness checks. Firstly, the lag order of ADF tests is changed from $L = 0$ to $L = 3$, and the results of the SADF and GSADF tests significantly reject the null hypothesis that there is no bubble at the 5% level, indicating that there are multiple bubbles in iron ore and stock markets during the full sample period. From the robustness check results, the change of lag order would not affect the findings, which means that the results are robust.

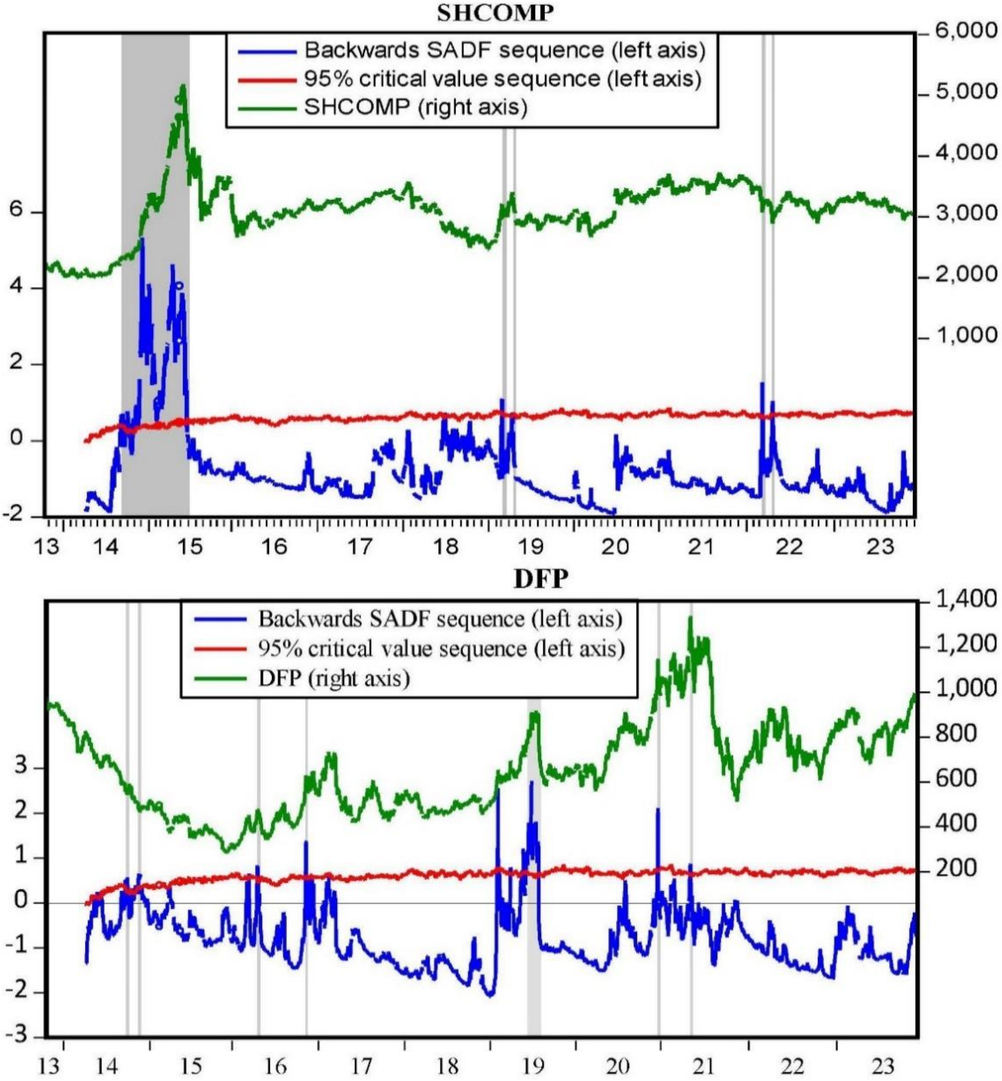
Table 4. Results of ADF tests with lag order $L = 3$

Variable	SADF test	GSADF test
SFP	1.713**	4.156***
CSI300	4.578***	5.645***
DFP	1.674**	2.704**
SHCOMP	4.323***	5.312***
1% critical value	2.141	2.951
5% critical value	1.565	2.511
10% critical value	1.294	2.279

*Notes: *** and ** indicate significance at the 1% and 5% levels, respectively.*

Next, as mentioned previously, besides the SFP and CSI300, the DFP and SHCOMP also can be used as alternative variables for international iron ore price and China's stock index. Consequently, the DFP and SHCOMP will be used to examine the robustness of the empirical analysis. Figure 5 indicates that the results of bubble detection are basically consistent with the previous results, with a bit of a difference in the date-stamping of bubbles, thus confirming the robustness of the study findings.

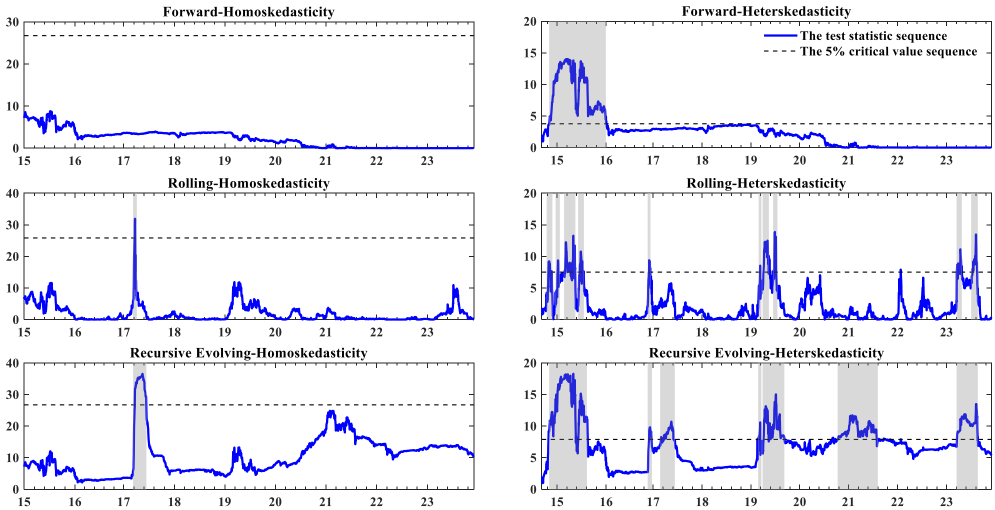
Figure 5. Bubble periods in SHCOMP and DFP



Notes: the green line is the SHCOMP and DFP, and the shaded areas are its bubble periods.

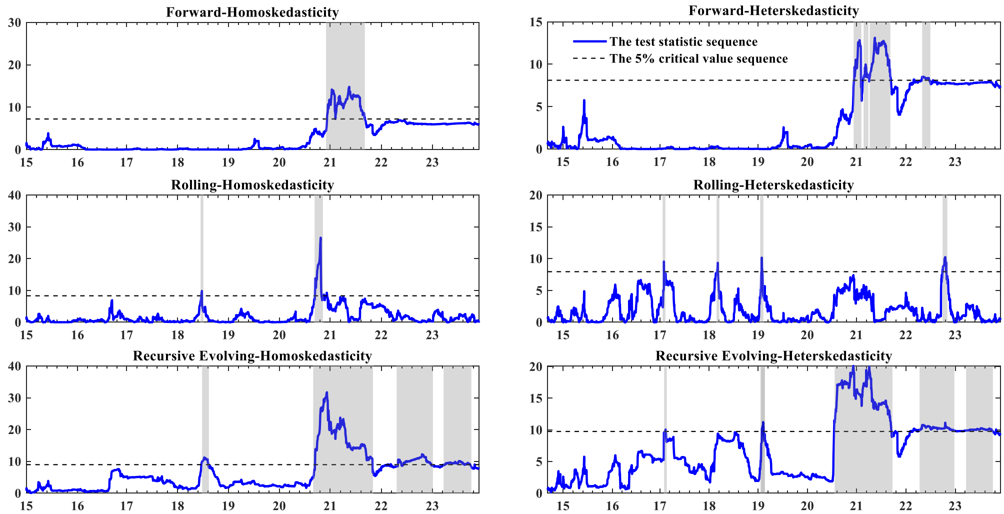
Finally, the minimum window size f_0 is changed from 0.1 to 0.15, which contains 359 observations, and the results in Figures 6 and 7 show the causal relationships between iron ore and China's stock markets, which are remarkably consistent with earlier empirical analysis. In combination with Table 3, this paper finds three bubble contagions between these markets according to two conditions of the bubble contagion effect. There are two unidirectional contagions, which are the first bubble contagion from iron ore to stock market in 2014 and the second one from stock to iron ore in 2019, and the bilateral contagion effect of bubble appeared in late 2020. As a consequence, the change of the minimum window size does not influence study results, revealing the robustness of the findings.

Figure 6. Tests for Granger causality from SFP to CSI300 ($f_0 = 0.15$)



Notes: The blue lines are the test statistic sequence; the dotted lines denote the 5% critical value sequence, and the shaded areas are causal periods; The arrow indicates the occurrence date of bubble.

Figure 7. Tests for Granger causality from CSI300 to SFP ($f_0 = 0.15$)



Notes: The blue lines are the test statistic sequence; the dotted lines denote the 5% critical value sequence, and the shaded areas are causal periods; The arrow indicates the occurrence date of bubble.

7. Conclusion and policy implications

As a critical raw material for industrial production, iron ore price shifts have important impacts on stock markets and economies of importing countries. With the development of iron ore derivatives markets, more and more attention from institutional investors is put on portfolio allocation between iron ore and stocks. Capital flow and message transfer among these markets are increasingly becoming more frequent, which increases the probability of risk spillover. Most existing studies have adopted static models and examined the general link between stock and commodities markets, such as return link and volatility spillover, but no such studies have analyzed the bilateral risk spillover effect by examining the possibility of multiple bubbles and identifying contagion effect among iron ore and stock markets. As a result, this paper detects the multiple bubbles and identifies the time and duration of bubbles based on the GSADF and BSADF tests. Moreover, the time-varying Granger causality tests are used to investigate the dynamic contagion of bubbles among the studied markets.

The main conclusions are summarized as follows. First, there are multiple bubbles in each of these two markets over the period studied, and the initiation and termination of bubbles are tightly connected to market liquidity and investor's expectation. Second, three episodes of bubble contagion are available. The contagion direction of first bubble is from iron ore to China's stock market and the reverse direction for second, and the substitution effect has been changed into a linkage effect since 2019 between these markets. Third, there is a bi-directional contagion correlation among markets in the post-COVID-19 era, which provides evidence for the financialization of iron ore market.

Based on the research findings, this study proposes policy recommendations for investors and identifies limitations of the current methodology as follows: (1) The degree of financialization of the iron ore market is deepening, and the impact from global financial markets has intensified the extraordinary volatility of the iron ore market. Therefore, market participants need to strengthen their risk awareness and timely adjust their investment portfolio strategies, such as adding some assets whose prices are weakly correlated with the iron ore and stock prices, such as gold and bonds, to avoid linkage effects between asset prices. (2) the empirical analysis employing time-varying Granger causality tests reveals that bubble contagion between iron ore and stock markets exhibits considerable variation over time, demonstrating that portfolio diversification strategies must be time-varying as well. (3) Detecting bubbles requires the BSADF procedure and the reverse regression procedure, which is complex and computationally inefficient. In order to further improve the performance of the method, future research should focus more on improving the methodology for estimating the dates of bubble episodes and increasing the crisis detection rate. (4) This paper employs a bootstrap-based contagion detection framework to identify the existence of bubble contagion in an ex post manner. It is hoped that subsequent research will develop a real-time monitoring system capable of detecting the change from market stability to contagion states. The implementation of such real-time detection capability could open new research avenues in financial applications.

Acknowledgement

This research was supported by Major project of National Social Science Foundation (No. 23ZDA062).

References

Ahmed, A. and Huo, R., 2021. Volatility transmissions across international oil market, commodity futures and stock markets: Empirical evidence from China. *Energy Economics*, 93, 104741.

Asadi, M. Tiwari, A.K. Gholami, S. Ghasemi, H.R. and Roubaud, D., 2023. Understanding interconnections among steel, coal, iron ore, and financial assets in the US and China using an advanced methodology. *International Review of Financial Analysis*, 89, 102789.

Asadi, M. Roudari, S. Tiwari, A.K. and Roubaud, D., 2023. Scrutinizing commodity markets by quantile spillovers: A case study of the Australian economy. *Energy Economics*, 118, 106482.

Balcilar, M. Ozdemir, Z.A. and Shahbaz, M., 2018. On the time-varying links between oil and gold: New insights from the rolling and recursive rolling approaches. *International Journal of Finance & Economics*, 24(3), pp.15-35.

Ben, D.I. and Azrak, T., 2023. The bubble contagion effect between crude oil and oil-exporting stock markets: the case of GCC countries. International Journal of Emerging Markets, 18(1), pp.1-19.

Bian, J. He, Z. Shue, K. and Zhou, H., 2018. Leverage-Induced Fire Sales and Stock Market Crashes. *NBER Working Paper*, No. 25040.

Brooks, C. Prokopczuk, M. and Wu, Y., 2015. Booms and Busts in Commodity Markets: Bubbles or Fundamentals?. *Journal of Futures Markets*, 35 (10), pp.916-938.

Burdekin, R.C.K. and Tao, R., 2021. From shanghai to Sydney: Chinese stock market influences on Australia. *Finance Research Letters,* 38, 101502.

Chen, Y. and Yang, S., 2021. Time-varying effect of international iron ore price on China's inflation: A complete price chain with TVP-SVAR-SV model. *Resources Policy*, 73, 102200.

Chen, Y. and Yang, S., 2022. How does the reform in pricing mechanism affect the world's iron ore price: A time-varying parameter SVAR model. *Romanian Journal of Economic Forecasting*, 25(2), pp.83-103.

Creti, A. Joëts, M. and Mignon, V., 2013. On the links between stock and commodity markets' volatility. *Energy Economics*, 37, pp.16-28.

Diba, B.T. and Grossman, H.I., 1988. Explosive rational bubbles in stock prices?. *American Economic Review,* 78, pp.520-530.

Eichengreen, B., 2013. Currency war or international policy coordination. *Journal of Policy Modeling*, 35(3), pp.425-433.

Erb, C. and Harvey, C., 2006. The Strategic and Tactical Value of Commodity Futures. *Financial Analysts Journal*, 62(2), pp.69-97.

Etienne, X.L., 2017. Irrational exuberance in the Chinese iron ore market?. *Applied Economics Letters*, 24(16), pp.1161-1166.

Evans, G.W., 1991. Pitfalls in testing for explosive bubbles in asset prices. *American Economic Review*, 81(4), pp.922-930.

Fama, E.F., 1970. Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2), pp.383-417.

Gannon, G., 2005. Simultaneous volatility transmissions and spillover effects: U.S. and Hong Kong stock and futures markets. *International Review of Financial Analysis*, 14(3), pp.326-336.

Gharib, C. Mefteh-Wali, S. and Jabeur, S.B., 2021. The bubble contagion effect of COVID-19 outbreak: Evidence from crude oil and gold markets. *Finance Research Letters*, 38, 101703.

Gomez-Gonzalez, J. Hirs-Garzon, J. and Gamboa-Arbelaez, J., 2020. Dynamic relations between oil and stock market returns: A multi-country study. T*he North American Journal of Economics and Finance*, 51, 101082.

Gomwe, C. and Y. Li., 2019. Iron ore price and the AUD exchange rate: A Markov approach. *The Journal of International Trade & Economic Development*, 29(1561), pp.1-16.

Gorton, G. and Rouwenhorst, K.G., 2006. Facts and Fantasies about Commodity Futures. *Financial Analysts Journal*, 62(2), pp.47-68.

Gutierrez, J.P. and Vianna, A.C., 2018. Price effects of steel commodities on worldwide stock market returns. *The North American Journal of Economics and Finance*, 51, 100849.

Gürkaynak, R.S., 2008. Econometric tests of asset price bubbles: Taking stock. *Journal of Economic Surveys*, 22(1), pp.166-186.

Hamilton, J.D. and Whiteman, C.H., 1985. The observable implications of self-fulfilling expectations. *Journal of Monetary Economics*, 16(3), pp.353-373.

He, C. Gao, Y. Xiao, F. Tang, L. and Khan, Y., 2024. A bubble identification mechanism: Evidence from the Chinese stock market. *Pacific Economic Review*, 29(1), pp.55-87.

Hoang, N. and Nguyen, B., 2018. Oil and iron ore price shocks: what are the different economic effects in Australia?. *Economic Record,* 94(305), pp.186-203.

Jarrow, R.A. Protter, P. and Roch, A.F., 2012. A liquidity-based model for asset price bubbles. *Quantitative Finance*, 12(9), pp.1339-1349.

Ji, H. and Zhang, H., 2024. Application of the LPPL model in the identification and measurement of structural bubbles in the Chinese stock market. *North American Journal of Economics and Finance*, 70, 102060.

Jowitt, S., 2020. COVID-19 and the global mining industry. *SEG Discovery*, 122, pp.33-41.

Kim, Y. Ghosh, A. Topal, E. and Chang, P., 2023. Performance of different models in iron ore price prediction during the time of commodity price spike. *Resources Policy*, 80, 103237.

Li, X. and Wei, Y., 2018. The dependence and risk spillover between crude oil market and China stock market: new evidence from a variational mode decomposition-based copula method. *Energy Economics*, 74, pp.565–581.

Li, Y. Wang, S. and Zhao, Q., 2021. When does the stock market recover from a crisis?. *Finance Research Letters*, 39, 101642.

Long, J. Yuan, X. Jin, L. and Zhao, C., 2024. Connectedness and risk spillover in China's commodity futures sectors. *Journal of Futures Markets*, 44(5), pp.784-802.

Lucas, R.E., 1978. Asset prices in an exchange economy. Econometrica, 46, pp.1429-1445.

Ma, Y.Q. and Wang, J.H., 2021. Time-varying spillovers and dependencies between iron ore, scrap steel, carbon emission, seaborne transportation, and China's steel stock prices. *Resources Policy*, 74, 102254.

Ma, W. Zhu, X. and Wang, M., 2013. Forecasting iron ore import and consumption of China using grey model optimized by particle swarm optimization algorithm. *Resources Policy*, 38(4), pp.613-620.

Meng, S. Fang, H. and Yu, D., 2020. Fractal Characteristics, Multiple Bubbles, and Jump Anomalies in the Chinese Stock Market. *Complexity*, 2020(9), pp.1-12.

Mensi, W. Beljid, M. Boubaker, A. and Managi, S., 2013. Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. *Economic Modelling*, 32, pp.15-22.

Phillips, P.C.B. Wu, Y. and Yu, J., 2011. Explosive behavior in the 1990s Nasdaq: When did exuberance escalate asset values?. *International Economic Review*, 52, pp.201–226.

Phillips, P.C.B. Shi, S. and Yu, J., 2015a. Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P 500. *International Economic Review*, 56, pp.1043-1078.

Phillips, P.C.B. Shi, S. and Yu, J., 2015b. Testing for multiple bubbles: Limit theory of real-time detectors. *International Economic Review*, 56, pp.1079-1134.

Radetzki, M. Eggert, R.G. Lagos, G. Lima, M. and Tilton, J.E., 2008. The boom in mineral markets: How long might it last?. *Resources Policy*, 33(3), pp.125-128.

Shi, S. Phillips, P.C.B. and Hurn, S., 2018. Change detection and the causal impact of the yield curve. *Journal of Time Series Analysis*, 39(6), pp.966-987.

Shu, M. and Zhu, W., 2020. Detection of Chinese stock market bubbles with LPPLS confidence indicator. *Physica A: Statistical Mechanics and its Applications*, 557, 124892.

Sornette, D. Demos, G. Zhang, Q. Cauwels, P. Filimonov, V. and Zhang, Q., 2015. Real-time prediction and post-mortem analysis of the Shanghai 2015 stock market bubble and crash. *Journal of Investment Strategies*, 4(4), pp.77-95.

Summers, L.H., 1986. Does stock market rationally reflect fundamental values?. T*he Journal of Finance*, 41(3), pp.591-601.

Su, C. Wang, K. Chang, H. and Dumitrescu–Peculea, A., 2017. Do iron ore price bubbles occur?. *Resources Policy*, 53, pp.340-346.

Swanson, N.R., 1998. Money and output viewed through a rolling window. *Journal of Monetary Economics*, 41(3), pp.455-474.

Tang, K. and Xiong, W., 2012. Index investment and the financialization of commodities. *Financial Analysts Journal*, 68(5), pp.54-74.

Thoma, M.A., 1994. Subsample instability and asymmetries in money-income causality. *Journal of Econometrics*, 64(1-2), pp.279-306.

Meng, S. Fang, H. and Yu, D., 2020. Fractal Characteristics, Multiple Bubbles, and Jump Anomalies in the Chinese Stock Market. *Complexity*, 2020(9), pp.1-12.

Wen, F. Cao, J. Liu, Z. and Wang, X., 2021. Dynamic volatility spillovers and investment strategies between the Chinese stock market and commodity markets. *International Review of Financial Analysis*, 76, 101772.

Wårell, L., 2018. An analysis of iron ore prices during the latest commodity boom. *Mineral Economics*, 31, pp.203-216.

Younis, I. Cheng, L. Basheer, M.F. and Joyo, A.S., 2020. Stock market comovements among Asian emerging economies: A wavelet-based approach. *PLOS ONE*, 15(10), pp.1-23.

Zhao, Y. Chang, H. Su, C. and Nian, R., 2015. Gold bubbles: when are they most likely to occur?. *Japan and the World Economy*, 34-35, pp.17-23.

Zhao, Z. Wen, H. and Li, K., 2020. Identifying bubbles and the contagion effect between oil and stock markets: New evidence from China. *Economic Modelling*, 94, pp.780-788.

Zhen, S. Wu, Q. and Wang, X., 2017. *Excessive co-movement effect and evolution network analysis of Chinese stock market*. IEEE/SICE International Symposium on System Integration(SII), Taipei, Taiwan, pp.220-225.