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The Evolution of Efficiency in the Chinese Stock Market

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Approval of the Dissertation Committee

This dissertation has been duly read, reviewed, and critiqued by the Committee listed below, which hereby approves the manuscript of Qiyun Li as fulfilling the scope and quality requirements for meriting the degree of Doctor of Philosophy in Economics.

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Abstract

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This dissertation examines the weak-form efficiency of the Chinese stock market and provides evidence on how the market efficiency evolved throughout the last three decades. The Shanghai Composite Index (SSEC) and the Shenzhen Component Index (SZSE) are the primary indicators of the Chinese stock market in this study. Both traditional economics and the complex systems' methods are employed to evaluate market efficiency, with an additional focus on the effect of two parameter inputs (embedded dimension and noise filter) on entropy methods to improve their ability to detect phase transitions in stock market data. The traditional efficiency tests indicate that the Chinese stock market during the full sample period of 1990-2021 is inefficient, but some of the sub-sample periods indicate the weak-form efficiency, except for the ADF test. Meanwhile, the complex systems' methods suggest that the level of randomness in returns increases over time. Additionally, I find that the bull periods of the Chinese market are less efficient than the bust periods, which may indicate that investors tend to commit more errors during the bull period. Generally, the study concludes that the complex systems' methods provide a more comprehensive evaluation of the changes in the market efficiency than traditional methods. The empirical results suggest that the Chinese stock market is not completely efficient based on the traditional efficiency tests but the level of efficiency has improved over time based on the evidence of the complex systems' analysis.

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Chapter 1 Introduction

This dissertation examines the weak-form efficiency of the Chinese stock market over a 30-year period and provides evidence that the markets evolve dynamically under a complex environment. The Efficient Market Hypothesis (EMH) suggests the definitions of financial markets efficiency. Depending on the information set availability, the weak-from of EMH has been tested in terms of whether all past prices and transactions' based information are already reflected in stock prices, and thus technical trading strategies are unlikely to beat the market. To quote Fama (1965), "the past history of series of shares prices changes cannot be used to predict the future in any meaningful way". The traditional methods of testing the random walk hypothesis, a specific version of the weak-form of EMH, assert that stock prices move randomly and are unpredictable based on past data. By testing the random walk hypothesis, the study aims to determine whether price changes in the Chinese stock market can be predicted. If the results indicate that the Chinese stock market does indeed exhibit a random walk pattern, there are no recurrent patterns in series and investors cannot predict future stock prices based on historical prices.

In addition to traditional tests of efficiency, the complexity methods are used to evaluate the efficiency of the market, and the results are compared and contrasted. The traditional methods include serial correlation, the ADF unit root test, runs tests, and the variance ratio test, while the complexity methods include permutation entropy, sample entropy, approximate entropy, and hurst exponent. Entropy methods can provide a way to measure the complexity of the financial market dynamics and can be used to assess the degree of randomness or degree of predictability of the series. The high value of entropy indicates the series deviates less from a random process and there are no significant patterns or regularities in the data. The study also explores the effect of different parameter inputs on entropy models, with the goal of improving their ability to detect phase transitions in the stock market data.

The Shanghai Composite Index and the Shenzhen Component Index serve as the primary indicators of the Chinese stock market in this study. Data for the Shanghai Composite Index is available from December 20, 1990 to July 7, 2021, while data for the Shenzhen Component Index is from January 24, 1995 to July 7, 2021.

1.1 Background of the Study

Eugene Fama's paper "Random Walks in Stock Market Prices" (1965) has been published 55 years, and the significant influence of the efficient market hypothesis (EMH) is still being felt today. For investors and trade regulatory organizations, verifying the EMH is still important in determining whether market participants are able to achieve abnormal returns, and to identify any potential market inefficiencies or strategies that may lead to outperformance against buy-and-hold strategies. When EMH holds, financial markets are efficient and it is very difficult for investors to consistently beat the market over the long run and for security prices to be predicted (Malkiel, 1973). However, as discussed in Malkiel's book "A Random Walk Down Wall Street" (1973), even if markets pass efficiency tests, it doesn't guarantee that they set the correct price, and bubbles may still occur. The critical implication of the EMH is that arbitragers in the market can help eliminate the excess return by selling against a given trading opportunity.

To test the weak-form of EMH, the random walk hypothesis has been proposed, which states that prices must follow a random walk pattern to eliminate the possibility of gains from past information-based trading. The common methods of testing the random walk hypothesis are autocorrelation (such as the Ljung-Box test, Box-Pierce test), variance ratio runs and unit root tests. A significant amount of scholarly research on the EMH has concentrated on testing that prices exhibit random walk behavior by examining the predictability of security returns based on historical price changes. To test the level of market efficiency, entropy, a complex systems' measure of disorder, has been used in various applications. The use of entropy helps quantify the market's efficiency and determine if the degree of efficiency has been improved over time.

The limited research on the evolutionary efficiency of China's stock market motivated me to study the time-varying degree of efficiency in China's market and compare it with traditional methods to test its weak-form efficiency. As a large and rapidly developing emerging market, China's stock trading patterns and market behavior have a huge impact on the world economy. Several factors in the Chinese stock market might be responsible for its perceived inefficiency. Firstly, the Chinese stock market is dominated by individual investors instead of institutional investors, and inexperience and errors of individual investors may contribute to mispricing of securities leading to a disconnect between share prices and economic conditions. Secondly, many publicly listed Chinese companies had a high level of state ownership, particularly before the split share reform in 2005. Chinese companies often exhibit a concentrated ownership structure, limited disclosure, weak investor protection, and reliance on the banking system, which can lead to a lack of transparency and market inefficiencies (Yu, 2012). Furthermore, the limited availability of short-selling mechanisms leaves investors without efficient instruments to hedge their risks or express their views on stock valuations. Lastly, government intervention and information asymmetry can distort the pricing mechanism and contribute to market inefficiency.

The Chinese stock market's two major boom and bust periods provide an opportunity to study its adaptive behavior in response to crises. If a market becomes more efficient after a crisis or major crash, it indicates that markets indeed exhibit signs of an evolving system, where participants learn over time.

1.2 Purpose of the Study

The study seeks to answer the following research questions:

1. Is the weak-form of EMH supported for China's stock market data of the sample periods tested?
2. Does the entropy method provide a more comprehensive evaluation of the evolution of market efficiency in China's stock market over time?
3. What is the degree of market efficiency across different time periods and varying market conditions?
4. Can entropy be used as a reliable index to detect phase changes in the market?

The study tests the weak-form of EMH in China's stock market by applying traditional methods to the full time length and sub-sample periods of the Shanghai and Shenzhen stock markets. It then evaluates the evolutionary efficiency of the market using three entropy methods and the Hurst exponent. Finally, the study uses simulated time series to test the sensitivity of entropy methods for detecting randomness in security series. The whole time period in this study for the Shanghai market is daily index prices from 1990-12-20 to 2021-07-07, while for the Shenzhen market covers the sample is from 1995-01-24 to 2021-07-07. The Shanghai Composite index has been available since 1990-12-20 and the Shenzhen Component index has been available since 1995-01-24. To analyze efficiency across various market conditions, both markets are segmented into five sub-sample periods by combined boom-and-bust and regular periods. This approach allows for a thorough evaluation of market efficiency during these distinct phases, encompassing both bull and bust periods for each market.

1.3 Overview of Methodology

This study implements a variety of market efficiency tests for the Shanghai and Shenzhen indices, with the aim of determining whether the Chinese stock market rapidly incorporates available information and whether the price is unpredictable based on past data. The data samples of the indexes are divided into 5 sub-sample periods: regular and boom-and-bust periods, these will be defined in the empirical section. Traditional methods applied include serial correlation test, unit root test, variance ratio test, and runs test. In addition, the study employs three entropy methods (permutation entropy, approximation entropy, and sample entropy) to evaluate the adaptive market hypothesis. Results are presented using a 126-day rolling window, with entropy values calculated for each period to be compared with traditional methods. The Hurst exponent is also calculated using rescaled range analysis, which helps determine whether the series is exhibiting mean-reverting or momentum behavior and assesses the presence of long-term memory.

1.4 Significance of the Study

The study aims to test the evolutionary efficiency in China's market and bridge the gap of employing entropy methods to test the adaptative market hypothesis analysis in China's stock market. Comparing results of combined boom-and-bust periods, , regular time periods and separate boom and bust phases brings a new perspective to understand market efficiency of China's stock markets. Lastly, the entropy analysis of simulated time series provides the sensitivity of entropy methods.

1.5 Outline of the Study

The study is structured into the following chapters. Chapter 2 outlines key events which improved market liquidity and openness in China's stock market. Chapter 3 provides a review of past research on testing China's stock market efficiency, highlighting conflicting results from traditional methods and limited studies on market efficiency evolution. Chapter 4 details data and methodologies used in the study, including a simulation experiment designed to verify whether entropy methods can detect phase transitions between random and deterministic series, while also exploring the optimal selection of entropy method parameters when testing financial data. In Chapter 5, the study presents an analysis of empirical findings from traditional methods, entropy methods, and Hurst exponent across the whole sample period and the 5 sub-sample periods. The results of time-varying entropy methods with a rolling window also are included in this chapter. The last chapter provides a summary of the study's results and suggests directions for future research.

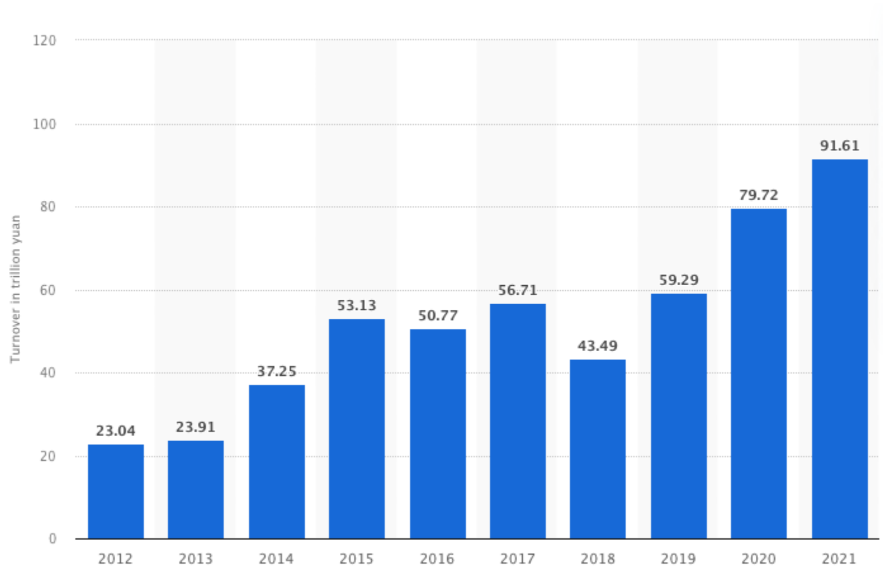
Chapter 2 The Introduction of Chinese Stock Market Indices

2.1 Development of the Chinese Stock Market

The total value of China's stock market reached a historic high of over 91 trillion yuan in 2021, surpassing the previous highs during equity bubbles in 2015 and 2008, and ranking it as the world's second largest (Figure 1). Over nearly 30 years of dynamic growth, the market has undergone structural changes, financial reforms, and increased market openness. This development has gone through a series of major stages.

Figure 1. The total market capitalization of China's stock market from 2012 to 2021(in trillion yuan)

The data source is Statista.com



The early stages of the Chinese stock market's development took place between 1983 - 1991. The government started allowing enterprises to issue bonds and stocks through over-the-counter (OTC) transactions in the early 1980s. In 1984, Shanghai Feile Acoustics Equipment Producing Co. became the first company to issue public offerings, with 10,000 shares at 50 yuan each. Later year, Shanghai Yanzhong Industrial Co. issued 100,000 shares of stock (50 yuan per share) to individuals, state and collective enterprises. There was significant demand for securities brokerages and trading as the number of securities issued and investors increased. In 1986, Shenyang Trust & Investment Corporation (TIC) became the first company to offer brokerage services for trading stocks and bonds. The demand for securities brokerages and trading grew as the number of securities issued and investors increased, leading the government to establish stock exchanges to support the rapid development of economic growth and provide new sources of funding for corporations and individuals.

The Shanghai Stock Exchange (SSE) was established in December 1990, while the Shenzhen Stock Exchange (SZSE) was established in July 1991. At the end of 1991, the Shanghai stock exchange had 8 listed stocks, while the Shenzhen stock exchange had 6 listed stocks. Fast forward to the present, the Shanghai stock exchange now has 1684 listed stocks, while the Shenzhen stock exchange has 1553. The Shanghai Stock Exchange is located in Shanghai, China's most important financial center. In contrast, the Shenzhen Stock Exchange is located in Shenzhen, the first and most important special economic zone in China, near Hong Kong. The SSE has a larger market capitalization than the SZSE, primarily because many of the listed stocks on the Shanghai Stock Exchange are state-own enterprises and basic industries enterprises. On the other hand, the stocks listed on the SZSE primarily consist of small and medium-sized enterprises, high-tech firms, and private companies. Therefore, that also caused the two markets to have different concentrations. The SSE is more focused on large-cap and state-owned enterprises, such as finance and energy, while the SZSE emphasizes smaller, growth-oriented companies in the technology and consumer industries.

The SZSE launched the Shenzhen Composite Index on April 4, 1991, with a base of 100 points and including all stocks traded on SZSE. On July 20, 1994, SZSE launched the SZSE component index as a primary index to reflect the performance of the Shenzhen stock market. It takes the previous day as the base of 1000. The Shenzhen component index initially consisted of 40 stocks, which expanded to 500 stocks on May 20, 2015 to meet market development needs. Similarly, SSE launched the Shanghai Composite index on July 15, 1991, with a base of 100 using December 19, 1990 and including all stocks in SSE. Both the Shanghai Composite index and the Shenzhen Component index track the performance of A-share and B-share listed companies. A-shares are for domestic investors and only can be purchased using Chinese currency, Renminbi.

B-shares, also known as RMB special stocks, are valued in Renminbi but only can be purchased by foreign investors using foreign currencies. The B-shares of the Shanghai Stock Exchange can be purchased with US dollars, while B-shares of the Shenzhen Stock Exchange can be purchased with Hong Kong dollars. After February 2001, B-shares became available to both domestic and foreign investors.

Compared to these two classes of shares, there are several different characteristics. Firstly, A-shares have higher liquidity than B-shares due to a larger participant base, resulting in an average trading volume in A-shares being 100 times that of B-shares. Meanwhile, there are more listed companies in A-shares than in B-shares. In SSE, there are only 44 B-share listed companies compared to 1679 A-share listed companies. Similarly, in the SZSE, there are 42 B-share listed companies as opposed to 1511 A-share listed companies. Secondly, before the policy allowing domestic investors to invest in B-shares, the primary investors in B-shares were large foreign institutional investors, while A-shares were dominated by individuals. However, after the policy announcement, individual investors began entering the B-share market. Compared to 2000, individual participation in B-shares increased by 333.07% in the first quarter of 2001. Lastly, information asymmetry exists between foreign investors and domestic investors. Foreign investors may have less information than domestic investors because of the disadvantage of language barriers or the lack of information from local firms, increasing the likelihood of herding behavior in the B-share market (Sharma et al. , 2015).

The second stage is from 1992 to 2001. Among many factors, four key elements are required for the stock market to operate efficiently: the exchange, the infrastructure, intermediaries and service providers, as well as regulatory agencies (Girardin & Liu, 2019). China initially set up the stock exchange, but without national regulation and law on stock trade. From 1992 to 2001, the Chinese government gradually established the different components and levels of China's securities market. In 1992, the government constituted the State Council Securities Commission (SCSC) and China's Securities and Regulatory Commission (CSRC) to lead the process of improving China's securities market system. China's government and CSRC heavily influenced the stock market's operations, and the complete system was gradually established. During the first 10 years, the Chinese stock market went through 5 bull markets induced by individual investor fascination by stock market trading and government interventions or reforms. Shanghai Composite Index increased from 386.85 in 1992 to 2184.37 in 2001. The trading settlement date changed from T + 0 to T +1 in 1995 and re-imposed 10% daily price limit rule in China's stock market to maintain stability and prevent market risks. In addition to the current A shares distributed to domestic investors, companies also were allowed to issue B-shares to foreign investors in 1992. But in early 2001, limitations on local investors purchasing B-shares were loosened. B-shares can be purchased and traded with relative simplicity by individual Chinese investors who have valid foreign currency accounts. Moreover, China's acceptance into the WTO in December 2001 also paved the way for greater openness of its financial markets to the world.

The third stage was the period between 2002 and 2008. Two significant events happened in this stage. The first event was the split-share reform in 2005, which converted non-tradable shares into tradable ones to address shareholding structure issues. Before 2004, non-tradable shares comprised two-thirds of the total share capital, with 70% belonging to state-owned entities. Due to the small scale of tradable shares, stock prices were easier to be manipulated and it is difficult to reflect a company's true value. The delay in split-share reform contributed to the prolonged bear market in the early 2000s. Shanghai composite index decreased from 2182 in 2001 to 1026 in the mid of 2005. In 2005, Chinese authorities announced the reform officially and the holders of non-tradable shares generally compensated the holders of tradable shares by giving out a portion of their shares at mutually-agreed prices. The reform has a positive effect on liquidity since the supply of tradable shares increased and it also benefits to construct of a more diverse ownership structure to improve the Chinese stock market to become a more mature and representative stock market. The second event was China’s gradual opening up of its capital market to foreign investors following WTO membership in 2001. In July 2003, the Chinese government launched the Qualified Foreign Institutional Investor (QFII) program to allow qualified foreign institutional investors to trade A-shares directly, not only limited to buying or sell in B shares. After the split-share reform that motivated optimistic investors and more foreign capital into the Chinese market, China’s stock market became a bull market from 2005 to 2007, with the Shanghai Index reaching a record high of 6124 on October 16, 2007. However, it was impacted by the Global Financial Crisis, resulting in a rapid drop to 1620 in November 2008.

The fourth stage of the Chinese stock market development was from 2009 to 2016. After the global financial crisis, the Chinese government implemented various stimulus policies to boost the economy, including tax cuts and increased investment in infrastructure. These measures helped to stabilize the stock market and lead to a strong recovery. In addition, the Chinese government continued to promote trading diversely and internationalization of the Chinese capital market. In 2010, with the implementation of margin trading and short selling in China’s stock market and the China authority's introduced CSI 300 futures to the market, China’s stock market officially entered the era of short selling. Margin trading and short selling are essential to improving the efficiency and completeness of the market, as well as the stability of the capital markets. In 2014, the authorities introduced the “Stock Connect” link between mainland China and international stock markets to reinforce China’s stocks' influence and to attract more international investors. The connection was first established between the Shanghai and Hong Kong markets in November 2014, and Shenzhen- Hong Kong link was in late 2016. It lessens the restrictions on foreigners buying China A-shares listed on the mainland and permits mainland China investors to purchase certain Hong Kong and Chinese companies listed in Hong Kong, which allowed for greater cross-border investment between China and Hongkong. For example, eligible domestic investors can trade eligible H-shares listed in Hong Kong. On the contrary, qualified international investors are allowed to trade eligible A-shares listed in Shanghai. The “Stock Connection” attracted more institutional investors into China’s stock market to weaken domestic individual investors' pricing power, which prevented the stock price from skyrocketing or falling suddenly. This also increased international interest in China’s stock market and attracted more foreign capital.

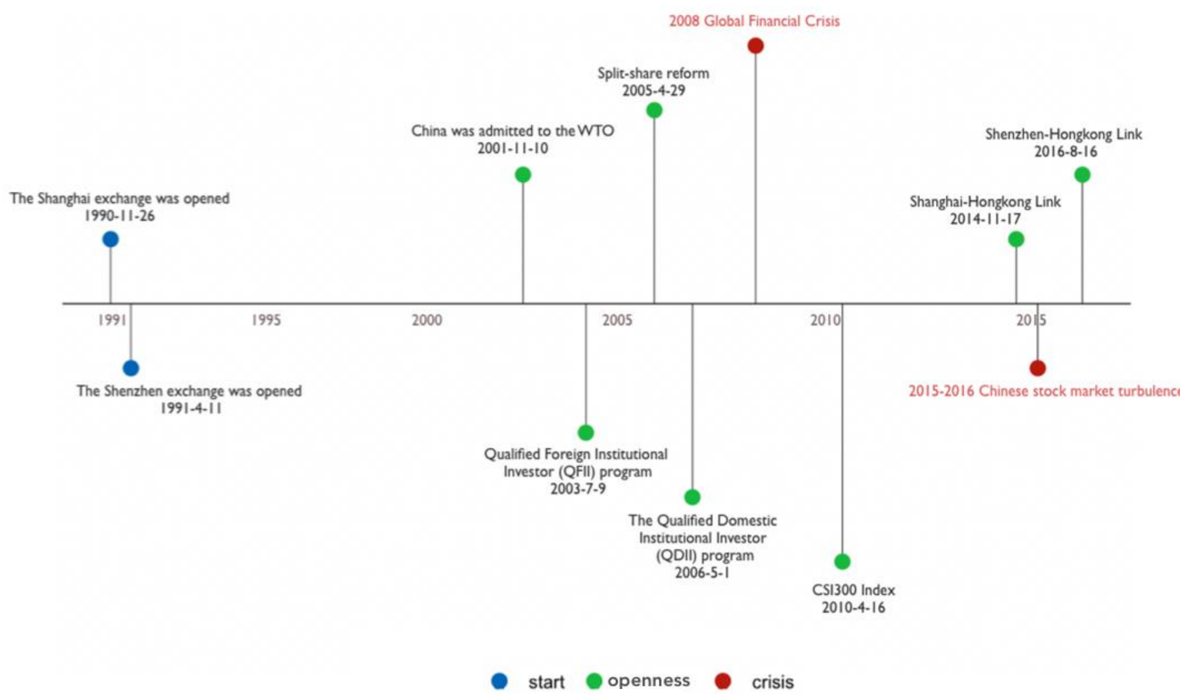
This period includes the second-largest boom and bust period in China stock market. A-share prices increased shapely from December 2014 to June 2015, which increased 60% in Shanghai Composite Index and 122% in Shenzhen Component Index. The highest point in the Shanghai stock market was 5178.19 point on June 12, 2015, and 18211.76 points in the Shenzhen stock market on June 15, 2015. After reaching the ceiling, China’s stock market began to crash until Feb 2016 to 2635 points in the Shanghai stock market and it decreased by 35%. This boom benefited from active market stimulation on the part of the government and the regulator, who loosened margin trading restrictions and reduced collateral requirements. Furthermore, starting in mid-autumn 2014, the People's Bank of China's monetary easing increased macroeconomic liquidity.

The final stage was from 2017 to current. It is the stage of China accelerating the internationalization process of China’s stock market. In June 2017, MSCI announced China A shares would be included in the MSCI Emerging Markets Index and the MSCI ACWI Global Index.

From 2017 to 2018, MSCI increased the overall weight of China and China A shares in the MSCI emerging market index about 41% and 5.1%, respectively (Zhen Wei, 2020). At the same time, FTSE Russell, S&P Dow Jones and other global indices have also added A shares. This demonstrates a significant advancement in the two-way opening of the Chinese capital market and it has been broadly acknowledged by foreign institutions and international capital. The Chinese government has been continuedly pursuing financial market reforms, including reducing market intervention, improving market efficiency, and promoting the healthy development of the stock market. Despite challenges such as the COVID-19 pandemic and trade tensions with the US, the Shanghai composite index has continued to grow and reached its all-time high in 2021.

Figure 2. The development timeline of China's stock market

The graph draws the timeline of major events in China's stock market. The blue dots means the start of the Shanghai and Shenzhen markets, the green dots display the events related to the reform and enhance the market openness, and the red dots are the two cresses in China's stock market.



2.2 Characteristics of the Chinese stock market

China’s stock market is often referred to as a “casino” due to its domination by individual investors and disconnection between share prices and economic conditions. According to China Securities Depository and Clearing (CSDC) data in 2016, institutional investors made up only 0.28% of the market, with the majority held by individual investors which are typically considered as inexperienced traders suffering with larger number of various errors. Such errors create price bubbles and inefficiencies in securities. This led to high market volatility due to speculative, short-term trading behavior. However, the trend has shifted, with the proportion of individual holdings declining to 39% at the end of 2020, while institutional investment has increased to 12.22%. Although still lower than in developed markets like the US (43.5%) and Hong Kong (51.7%), China's stock market is gradually transitioning from a "retail" market to an "institutional" market.

Second, the ownership structure in China’s stock market is complex. The share of listed companies can be classified into 5 parts: state-owned shares, legal person shares, employee shares, social public shares, and other shares. Among them, state-owned and legal person shares are around 60% of listed companies' total equities and non-negotiable shares. Only social public shares can be marketable, which is only a small part of shares in the total equities (Ma, 2001). But after the split share reform in 2005, the non-tradable shares converted to tradable shares and the reform significantly reduced the magnitude of the IPO underpricing issue (Khurshed et al. 2014).

Third, margin trading and short selling have a short history in China. When the Chinese Security Regulatory Commission permitted a select group of brokerage companies to short-sell 90 stocks on a designated list in March 2010, some of these concerns were partially allayed (Gao and Ding, 2019). The number of short sales surged significantly once short-sale refinancing became legal, but it started to decline again after 2015, even though the pilot program's enrollment was enlarged to 950 firms by the end of 2016. But with increasing the number of institutional investors and maturity of short selling market, the short selling eventually will benefit in price discovery and making markets more efficient.

Last but not least, China's stock market has several price movement restrictions. For example, the daily price increase and decrease limits. Chinese authorities limited the price change on regular stocks to 10% per day and 5% on special treatment stocks in order to keep the stock prices more stable. If the daily price changes over this threshold, the trading will stop on the stock.

Chapter 3 Review of Literature on Weak-Form of Market Efficiency

3.1 Efficient Market Hypothesis

The efficient market hypothesis (EMH), which relates to the market's capacity to convert information into prices, is a concept of informational efficiency. The EMH posits that it is impossible for investors to consistently achieve returns that are higher than the market average by using any publicly available information. According to Richard Thaler (2009), it can be divided into two parts: "no-free-lunch" and "the price is right". The latter concept assumes the market always has rational investors and unlimited arbitrageurs. Louis Bachelier (1990) first introduced the concept of efficient markets, which states that stock prices are random and unpredictable. Then, Paul Samuelson (1965) provided the first formal economic argument for "efficient markets" and mainly focused on the concept of a martingale rather than a random walk. Fama (1970) summarized EMH as "a market in which prices always fully reflect available information is called efficient", making it impossible for anyone to consistently beat the market by using available information. Fama also classified efficient market into three forms according to the different kinds of information sources: weak form, semi-strong form and strong form. In the weak form, market participants cannot use historical prices to predict securities' prices and receive excess returns because the prices already reflect all past information of assets. The semi-strong efficiency form stated that stock price fully reflects all publicly available information including past prices (e.g. financial statements, announcements of earnings and dividends, or stock splits, etc.). The strong efficiency form extends the hypothesis to a "perfect" market, meaning that even insiders cannot receive excess returns, thus stock prices fully reflect all the available information, both public and private.

In an analytical approach, the hypothesis of market efficiency aimed at explaining the price movement is hard to predict and it is also not possible to conceive of investment plans that will yield high returns. The weak form of the EMH is tested whether stock prices follow a random walk or a martingale. Most researchers focus on the random walk conditions to determine if asset returns follow this pattern.

The random walk was initially formulated as

$$p_t = p_{t-1} + r_t \tag{1}$$

where r_t is considered an independent and identically distributed process with mean 0 and constant variance. It asserts that price changes are random and unpredictable. But the stock price doesn't measure up with these conditions, as demonstrated by a number of studies. In 1997, Campbell et al. (1997) adjusted the formula of the random walk as

$$p_t - p_{t-1} = r_t = \mu + \epsilon_t. \tag{2}$$

The return r_t will be influenced by the constant term μ and an ϵ_t. Campbell, Lo and MacKinlay (1997) further distinguished the random walk into three sub-hypotheses on ϵ_t. The random walk 1 (RW1) requires ϵ_t to be an independent and identically distributed process with mean 0 and variance σ^2, or $\epsilon_t \sim IID(0, \sigma^2)$, which implies $r_t \sim IID(\mu, \sigma^2)$. The constant term μ

is the expected price change or drift. Under RW1 condition, most financial data will reject random walk since most financial time series violate the constant assumption of r_t. Random walk 2 (RW2) does not require an identically distributed condition. Hence $\epsilon_t$is an independent but not identically distributed process. Compared to RW1, RW2 is closer to the real world cases since it allows for unconditional heteroskedasticity in r_t. The random walk 3 (RW3) is the weakest form of the random walk hypothesis, which relax the condition of independent from RW2. ϵ_t or r_t is a process that is not independent or identically distributed but is uncorrelated. RW1 and RW2 are special condition of RW3.

3.2 Past literature review on the testing of EMH

The efficient market hypothesis (EMH) has been tested by numerous researchers using various methods. Fama (1970) tested the random walk of stock prices using serial correlations, runs tests and Alexander's filter technique and found evidence of a random walk in the market. Two decades later, instead of focusing on past returns, Fama (1991) used ratios and event study to test the semi-strong and strong form of EMH, such as dividend-price ratio, earnings-price ratio, book-to-market ratio and various measures of the interest rates. His result shows that prices are predictable from historical price, dividend yields and other structural variables. Fama & French (1988) found a mean-reverting negative serial correlation in NYSE market returns, indicating that stock returns are predictable. They mentioned that both serial correlation and runs test are not good for testing random walk hypothesis from a statistical or practical view by the following three reasons. First, these tests suffer from low statistical power, meaning that they may not be able to detect departures from random walk behavior even if they exist. Second, the results of these tests are sensitive to the choice of the lag length, which is an important parameter in the test specification. Third, the results of these tests can be influenced by outliers or non-stationary data, which can lead to incorrect conclusions about the random walk behavior of stock prices. Therefore, Fama & French argued that alternative methods, such as the variance ratio test, may be more appropriate for testing the random walk hypothesis in practice. Following this, Lo & MacKinalay (1988) introduced the variance ratio test as a more powerful tool for testing serial correlation of stock returns and found positive serial correlation in NYSE market returns and the random-walk model is strongly rejected. Today, the variance ratio test, along with serial correlation, unit root, and runs tests, is among the main linear methods used to test EMH.

Frennberg and Hansson (1993) used the variance ratio and autoregression tests to find positive autocorrelation in Swedish stock prices in the short term (1 to 12 months) and negative autocorrelation (mean reversion) in the long term. Borges (2011) tested market efficiency of the PSI-20 index in Lisbon stock market using serial correlation, runs test, ADF, and multiple variance ratio tests and found mixed results, but overall evidence of the stock market approaching a random walk behavior since 2000. Shaik (2016) selected 10 emerging Asian countries' stock indexes from 2001 to 2015 and separated the data into two periods: pre-crisis (2001-2007), and during & post-crisis (2008-2015). They employed 6 different unit root tests (ADF test, Phillips and Perron test, Kwiatkowski-Phillips-Schmidt-Shin test, Dickey-Fuller GLS (ERS) test, Elliot-Rothenberg-Stock Point-Optimal test, and Ng and Perron (2001) unit root tests). Based on unit root tests, they found that during the overall period 8 out of 10 Asian stock markets and during the pre-crisis period all 10 indexes followed the random walk. However, only 5 out of 10 Asian markets followed a random walk during the crisis and post-crisis period.

While the EMH has been widely studied and tested, there is a growing body of literature that challenges this hypothesis. Lo (2004) proposed the adaptive market hypothesis (AMH), which suggests that markets should not be seen as having perfect information processing, but rather as adaptive and evolving systems where individuals with limited information make decisions in a constantly changing environment. This results in a market efficiency that is not constant, but rather a dynamic concept that can change over time. It argues that the efficiency of financial markets is influenced by a variety of factors, including investor behavior and emotions, economic conditions, and technological advancement. In addition, natural selection plays a significant role in molding market participants in AMH. Investors are more likely to leave the market if they continually suffered losses in their previous investments (Lo, 2004). Moreover, unlike EMH, the AMH states arbitrage opportunities do exist from time to time due to the existence of trends, panics, bubbles, and crashes in the market.

Therefore, the key implication of the AMH is that market efficiency can vary over time based on changes in market environment. As a result, many recent studies of the AMH have attempted to explain how market efficiency levels vary over time. Studies have tested the AMH using two approaches: the first employs a time-varying model technique to gauge the degree of market efficiency (Noda 2016, Ito et al. 2016). Noda concludes the degree of market efficiency of the two Japanese stock markets changes over time and Ito et al. also found the degree of market efficiency varies over time in international stock markets. The second approach uses statistical testing with the moving window method to look into market efficiency (Urquhart & McGroarty 2016, Hiremath & Narayan 2016, Patra & Hiremath 2022). Hiremath & Narayan found the Indian stock market is moving towards efficiency by using the Generalized Hurst exponent with fixed and rolling windows. Patra & Hiremath (2022) employed the approximate entropy approach in a rolling window across the globe and concluded that stock market efficiency evolves over time.

3.3 Past Literature Review on Chinese Stock Market Efficiency

3.3.1 Contradictory results of testing EMH

Contradicting findings in the literature of the Efficient Market Hypothesis (EMH) are a common occurrence due to the use of differing methodologies and sample periods. Prior to 2000, most researchers found evidence of weak-form efficiency in the Chinese stock market, using methods such as serial correlation, unit root tests, variance ratios, and runs tests (Laurence et al., 1997, Liu et al., 1997, Long et al., 1999). In 1997, Laurence et al. tested weak-form efficiency in China's stock market on the indices of Shanghai A and B share index and Shenzhen A and B share index, and also examined the causal relationship between the Chinese stock market and those in Hong Kong and the US stock market. They concluded that the A share of both markets was efficient, but the B share was not. Liu et al. (1997) found that the Shanghai and Shenzhen stock exchanges indexes were individually efficient but collectively inefficient, due to a cointegration relationship between the two stock exchange indexes. Long et al. (1999) also found evidence of a random walk in both A and B shares markets by using the augmented Dickey-Fuller, variance ratio and runs test results. However, Darrat & Zhong (2000) used a model-comparison approach and found the opposite result, that both the Shanghai and Shenzhen markets were not random.

After the year 2000, several studies arrived at the conclusion that the Chinese stock market was not weak-form efficient. Ma and Barnes (2001) conducted a series of tests including serial correlation coefficient tests, runs tests and the 3 variance ratio tests of Lo and MacKinlay (1988) to examine the weak-form efficiency of both the Shanghai and Shenzhen stock markets (A and B shares) from 1990 to 1998. The results indicated that the daily returns of the four indices were highly correlated and did not follow a random walk, with B shares being found to be more predictable than A shares. As a result, they concluded that the Chinese stock market was not weak-form efficient.

Subsequent studies have supported these findings. Lima et al. (2004) implied variance ratio tests, robust to heteroskedasticity and bootstrap techniques, to examine the random walk hypothesis in Chinese, Hong Kong and Singapore markets. They found that the A shares and the Hong Kong market were weak-form efficient, but Singapore and the B shares of the Chinese stock market did not follow the random walk hypothesis. Niblock and Sloan (2007) analyzed the daily return of A and B shares in SSE and SZE and concluded that China's stock markets are not weak-form efficient. Charles and Darné (2009) used new multiple variance ratio tests, including the Whang-Kim subsampling, Kim's wild bootstrap tests and multiple Chow-Denning tests, to arrive at similar results, with the B shares found to be inefficient, while the A shares were deemed more efficient.

The most popular methodologies employed to test the random walk hypothesis are still linear methods, such as serial correlation, unit root test, variance ratio test, and runs test. However, There have been inconsistent results observed when applying different methodologies to the same market over the same time period. For instance, the unit root test has often produced contradictory results in comparison to other methods. In a study conducted by Worthington et al. (2005), the authors applied serial correlation, unit root, variance ratio and runs test to daily returns for 15 markets, consisting of 10 emerging markets (China, India, Indonesia, Korea, Malaysia, Pakistan, the Philippines, Sri Lanka, Taiwan and Thailand) and 5 developed markets (Australia, Hong Kong, Japan, New Zealand and Singapore). The results showed that all markets were weak-form inefficient as indicated by the serial correlation and runs test. The variance ratio test showed that none of the emerging markets were weak-form efficient, while only three of the developed markets (Hong Kong, New Zealand, and Japan) met the most stringent criteria for random walk efficiency. The unit root tests, however, suggested that all markets were weak-form efficient, except for

Australia and Taiwan. This conclusion was further reinforced by Liu (2011), who conducted market efficiency tests on China's and Hong Kong's stock markets from 2002 to 2009. The unit root test results showed that the Shanghai A shares were weak-form efficient, but Shanghai B shares, Shenzhen A and B shares are not weak-form efficient. In contrast, the variance ratio and runs test produced opposite results, indicating that Shanghai A shares were not weak-form efficient.

The limitations of unit root tests as a method for testing market efficiency are primarily due to the fact that they only consider the mean of returns and ignore the volatility of returns, which is an important factor in determining market efficiency. Unit root tests are commonly used to test the stationarity of financial time series. Additionally, unit root tests have a tendency to produce higher false positive results, which can lead to a deterministic series being tested having a unit root. Due to these limitations, unit root tests are not as effective as variance ratio tests or runs tests in determining market efficiency.

3.3.2 Testing the level of market efficiency

Given the conflicting results obtained through linear methods in testing the random walk hypothesis and the normal distribution assumption of random walk, scholars have been motivated to seek alternative methods from fields such as physics to better understand the level of randomness and uncertainty in the stock market. The first measurement is the Hurst coefficient or Hurst exponent, which is commonly used to detect long-term correlation and the self-similarity of a market. If long-range observations exhibit autocorrelation, it violates the efficient market hypothesis. From a statistical perspective, a market that is completely random has a Hurst exponent equal to 0.5, while a Hurst exponent greater than 0.5 indicates that the presence of long-term memory in the market, deviating from the random walk pattern and is considered inefficient. In this case, the market exhibits a tendency to persist in its current trend, either up or down, over periods of time, as evidenced by positive autocorrelation over longer time lags. Conversely, a Hurst exponent less than 0.5 indicates negative autocorrelation over longer time lag and a mean-reverting market. This suggests that, if the market has gone down in the past, there is a higher probability that it will reverse and move upward in the future.

Grech and Mazur (2004) used the local Hurst coefficient to measure the efficiency of the Dow Jones index and argued that the Hurst exponent is capable of detecting market crises. In addition, Cajueiro and Tabak (2004, 2005) employed the Hurst exponent to evaluate the efficiency of the stock markets in Asia and Latin America, and concluded that the Asian markets were more efficient than those in Latin America. The majority of the literature concurs that the Chinese stock market displays fractal structure and the presence of long-term memory features. Yang and Liu (2002) tested the fractal market hypothesis in the Shanghai and Shenzhen stock markets and found that the Hurst exponent of the two markets was 0.69 and 0.64, respectively, indicating that the two markets showed a trending behavior and they had a better than 50% chance to follow the trend with the historical moves. Wei Zheng (2013) also employed the Hurst exponent to study the Chinese stock markets and found that the Hurst exponent of Shanghai and Shenzhen stock markets was greater than 0.5, with a long memory of 300 trading days for the Shanghai market and 240 days for the Shenzhen markets. He concluded that the Chinese stock market has a memory of previous trading days and is inefficient.

However, it is worth noting that the R/S analysis is sensitive to outliers in the data and can present a biased evaluation of the Hurst exponent. Chu (2018) obtained a Hurst exponent of 0.298, indicating mean reversion in the stock series. Conversely, a few researchers have found that the markets follow a random walk with no fractal structure. Zhang & Huang (2001) conducted an empirical study on the Shanghai and Shenzhen stock market using R/S methods and found that the

Chinese stock market follows a biased random walk. Menggen (2003) also studied the long-memory effect in the Chinese stock market and the result showed there is no evidence of fractal structure and the market has no long-memory. Despite these findings, most studies conclude that the Chinese stock market has a fractal structure, with a Hurst exponent of approximately 0.65.

Another approach is information entropy. In 1948, Shannon proposed that the entropy of a system measures its level of randomness. For example, in the case of a fair coin with a 50% chance of getting tails and a 50% chance of getting heads, the entropy is 1 bit of information. However, if the coin has a 25% chance of getting tails and a 75% chance of getting heads, the entropy is 0.81. This indicates that the series can still be random, but the level of randomness is lower than in the fair coin scenario. When testing the random walk hypothesis, maximum entropy indicates that the observations are completely uncorrelated and disordered, and the stock prices are purely random, making the market weak form efficient. Conversely, if the entropy of the market does not reach its maximum value, the prices during this period are somewhat correlated and dependent, and the stock prices could be predicted based on historical prices, making the market inefficient.

In 1999, Gulko proposed using entropy to analyze financial time series, and demonstrated that the efficient market hypothesis could be operationalized and tested using the maximum-entropy formalism. Pincus and Kalman (1991, 2004) suggested that the approximate entropy (ApEn) method is useful for assessing financial time series efficiency and can be used as a market stability indicator. Additionally, Eom et al. (2008) found a significant negative correlation between ApEn and the Hurst exponent, implying that as the ApEn value increases, the Hurst exponent decreases, and the efficiency level of the market decreases.

ApEn's algorithm has two biases one is self-counting issue and the other is its dependanceon the length of the data series. Richman and Moorman (2001) defined Sample

Entropy SampEn) as a modified version of ApEn, which avoided self-counting bias. The two methods have been applied widely to test the market efficiency hypothesis. Mensi (2012) ranked 26 emerging stock markets' efficiency levels by employing modified Shannon entropy and rolling windows. He discovered a negative relationship between the financial crisis and stock market efficiency. Krisoufek and Vosvrda (2014) tested 38 stock indices' approximate entropy values. The Shanghai stock index rank at 26, which is higher than Spain and Singapore. But ApEn and SampEn methods have some limitations. Firstly, selecting the appropriate parameters. Calculating ApEn and SampEn requires selecting the two parameters, m and r. The parameter m is the embedding dimension size and determines the length of the sequences to be compared. r is the tolerance threshold for accepting similar patterns between two segments. Most financial time series papers use m =2 and r = 0.2 times the standard deviation of the series, but this is based on heart rate or hormonal release data, not financial series data. The second limitation is it is hard to find any papers to demonstrate how the approximate entropy and sample entropy can detect the market efficiency phase change, except in trading rule tests using entropy (Efremidze et al., 2021). Most studies have applied the concept of entropy to test financial asset data, but have not sufficiently demonstrated how the entropy method can distinguish varying levels of market efficiency. To address these limitations, I have conducted simulations using AR(1) models to examine the ability of entropy methods in detecting levels of randomness, as well as to determine appropriate parameters for analyzing financial time series data (as described in Chapter 5).

The Permutation Entropy (PE) method is used to quantify the level of randomness in a time series. A high PE value indicates that the time series is noisier and more random, while a lower PE value implies that the series is more deterministic. Unlike the ApEn and SampEn methods, which require the selection of two parameters, m and r, PE only requires the determination of the embedding dimension m. This simplicity in parameter selection makes PE a more convenient method for testing the randomness of a financial time series and evaluating the EMH. Additionally, research has shown that PE can be used as an early warning signal for market crashes. Hou et al. (2017) found that the PE value decreased significantly before market crashes occurred in the Shanghai and Shenzhen markets, providing a warning window of up to one year prior to the crashes. This highlights the potential utility of PE as a tool for detecting market inefficiencies and deviations from randomness.

3.3.3 The evolution in the efficiency of China's stock market

The examination of the evolution of China's stock market efficiency is an under-explored topic in the literature. One of the most widely studied subjects is the impact of the 2008 global financial crisis on the efficiency of the Chinese stock market. However, the findings are inconsistent due to varying sample periods used. For instance, Mahmood et al. (2010) found that the global financial crisis has no significant impact on the efficiency of the Chinese stock market. They applied ADF, DG-GLS, PP and KPSS tests on Shanghai and Shenzhen markets before (Jan 2004- June 2007) and during the crisis (July 2007- Dec 2009). The results showed that both markets were weak-form efficient and had unit roots in both the pre-crisis and crisis periods. On the other hand, Shaik & Maheswaran (2016) used a larger data sample size to investigate the changes in market efficiency in emerging Asian stock markets before (2001-2007) and after (2008-2015) 2008 global crisis. Their results showed that the Chinese stock market was weak-form efficient and followed a random walk during the pre-crisis period, but they could not find unit roots during the post-crisis period, meaning that the market was not weak-form efficient after the crisis.

However, to assert whether the Chinese market is becoming more or less deviates from efficient, we cannot only compare market efficiency before and after the crisis. Another approach is to use a moving window to examine market efficiency changes after major events in China's stock market history. Wang et al. (2009, 2010) employed detrended fluctuation analysis (MF-DFA) and found that both the Shanghai and Shenzhen markets were becoming more efficient after the price-limited reform. The length of each window was fixed to 1008 business days (about 4 years). Before the reform, the Hurst exponent varied between 0.4211 and 0.6349, while after the reform, the Hurst exponent was between 0.4762 and 0.5212. Zhu (2017) used linear models with rolling window and found that the Chinese market as a whole was inefficient. But most sub-samples' results demonstrate weak-form market efficiency and numerous periods with predictable returns were found.

On the other hand, some researchers have explored 'anomalies' that deviate from the EMH in the Chinese stock market. Research has shown that the Chinese stock market is subject to periods of overreaction. Two anomalies that have gained significant attention are long-term mean reversal and short-term momentum in equity returns. Wu (2011) supports the overreaction hypothesis in the Chinese stock market. They found that the Chinese stock market has strong mean reversion. A pure contrarian investment strategy creates excess returns and usually performs better than a pure momentum strategy. This can be explained by the positive-feedback trading framework. When good (bad) news is released, rational speculators, who expect future buy (sell) by positive-feedback trader, might decide to buy (sell) before noise traders. This early buying (selling) by rational speculators initiates positive-feedback trading, leading to short-term momentum. As a result, the market has a tendency to overreact to news. Additionally, Ho et al.(2022) mentioned that Chinese investors tend to follow the herd and leading to a more serious continuing overreaction in the market. They evaluate the relationship between information disclosure rating and continuing overreaction and argue that China's information disclosure system is not mature and comprehensive, and financially illiterate individual investors when exposed to large amounts of information, are unable to make rational decisions and tend to rely too much on official sources and follow the herd. Ni et al. (2015) found the herding behavior among Chinese investors. They investigate whether investors could make profits by using stochastic oscillator indicators (SOI) to trade stocks and discovered that investors may use momentum strategies, specifically by following overbought trading signals. They suggested that this behavior might be due to herding behavior among Chinese investors. The calendar effect also has been tested. Xiong (2019) examined four calendar effects in the China stock market using subsample analysis and rolling window analysis and found that the AMH gives a better explanation for the market dynamics in the Chinese stock market.

In summary, while some studies have examined the evolution of China's stock market efficiency, further research is needed. Moving window analysis can be a useful approach to examine changes in market efficiency after significant events. The Adaptive Market Hypothesis provides a better explanation for market dynamics in the Chinese stock market, and overreaction and herding are common occurrences that could be attributed to various factors, such as the lack of financial literacy and investing experience the information disclosure system, and changes in market environment.

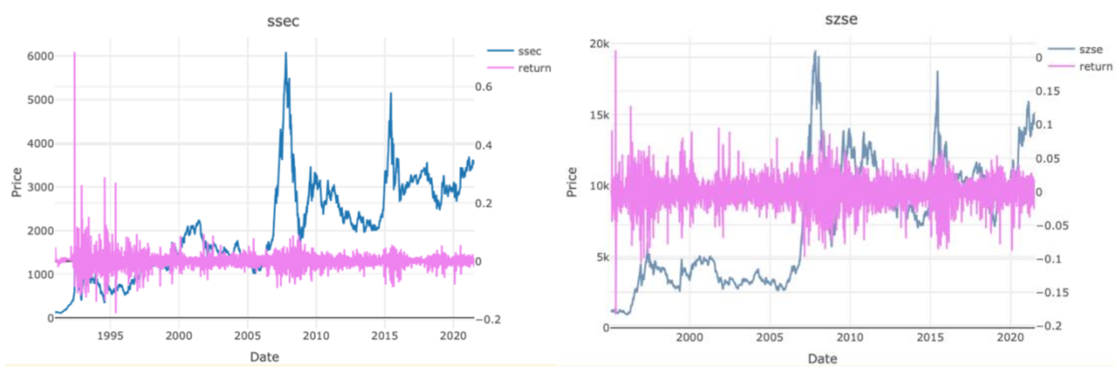
Chapter 4 Data and Research Methodology

4.1 Data and Hypotheses

The present study utilizes a data set comprising 7465 daily closing prices of the Shanghai Exchange Composite Index (SSEC) and 6418 daily closing prices of the Shenzhen Exchange component Index (SZSE). The data period for SSEC ranges from December 20, 1990 to July 7th, 2021, while the data period for SZSE is from January 24th, 1995 to July 7th, 2021. The data of daily price indices are collected from investing.com. Figure 3 presents the daily closing prices and returns for the two indices for the given time period. The returns for each series are measured by $r_t = \ln(p_t/p_{t-1})$, where r_t is the return at time t, p_t is the price at time t, and p_{t-1} is the time at t-1.

Figure 3. Time Series Plots of SSEC and SZSE's Price and Return

The graph displays the price and return time series plots of the SSEC and SZSE indexes. The full sample period of SSEC prices and returns used extends from December 1990 to July 2021, while the sample size for SZSE is from January 1995 to July 2021.



During the history of the Chinese stock market, both the Shanghai and Shenzhen stock indexes have experienced similar fluctuations. There have been two major upward trends and downturns: the first up and down is between 2005 to 2009, and the second is from 2014 to 2015. The split-share reform triggered a rapid increase in stock prices from 2005 to 2007, but this was followed by a significant decrease during the Global Financial Crisis from 2007 to 2009. The same pattern can be seen in the 2015 stock price turbulence for both markets. In terms of return time series, both indexes exhibit fluctuations around 0, with returns appearing more volatile during periods of significant increase and decrease. Before 1995, the SSEC index had returns ranging from 30% to -30%, but after 1995, the returns for both markets were mostly within the range of $\pm$5%.

Given the multiple significant structural changes and two significant boom and bust cycles that have the potential to impact stock market efficiency in the Chinese market, the full sample period for both markets has been divided into the following five sub-periods to analyze the evolution of market efficiency:

1) December 20, 1990 to December 31, 2004. It represents the stage before the 2008 boom and bust period. (For the SZSE, the period spans from Jan 24, 1995 to Dec 30, 2005)
2) January 4, 2005 to January 5, 2009. During this period, the SSEC was from 1200 points increased to the peak of 6000 points in October 2007, then the index decreased to 1900 points. Same for the Shenzhen stock market, the index started at 3000 points in 2005 and climbed all the way up to 19,000 points in October 2007, then declined to 6700 points at the beginning of 2009. (For the SZSE, the period spans from Jan 4, 2006 to Jan 5, 2009)
3) January 6, 2009 to March 31, 2014. This is the post-crisis period.
4) April 1, 2014 to June 1, 2016, the second large up and down period. Shanghai stock index increased from 2000 points in April 2014 to 5000 points in June 2015 and then decreased to 2800 points in June 2016. In the Shenzhen market, the stock index increased from 7500 points in April 2014 to 18,000 points in June 2015 and then decreased to 9000 points in June 2016. The Shenzhen market has more significant price fluctuation than the Shanghai market.
5) June 2, 2016 to July 7, 2021, after the 2015 market crash.

The aim of this study is to examine the evolution of market efficiency in China's stock market over time, while taking into account the impact of significant structural changes and boom and bust periods. Unlike many previous studies that separate their analysis into pre- and post-crisis periods, this study considers the combined effect of both periods to eliminate any influence that the boom and bust may have. The main research objective is to determine if China's stock market exhibits weak-form efficiency (follows a random walk), and to assess whether the market has become more efficient over time by comparing each stage.

4.2 Statistical Tests for Market Efficiency

In this study, I used four traditional (linear) statistical methods: serial correlation test, Augmented Dickey-Fuller unit root test, runs test, and variance ratio test to examine market efficiency for the whole period and each sub-period. The runs test is based on the test of IID assumption of the random walk increments (RW1), while the serial correlation test is based on the Ljung-Box test or variance ratio test to examine the uncorrelation condition on the return series of RW3. In addition, non-traditional models have been implied in this study. I implemented permutation entropy, approximate entropy and sample entropy models to evaluate the randomness of the series. These entropy methods do not follow the assumption of the random walk hypothesis and it can be applied to non-linear price series or return series. The entropy value indicates the similarity level of two neighboring segments and a higher entropy value refers to the series having a high level of randomness. Lastly, the Hurst exponent is employed to determine the pattern of series.

4.2.1 Serial correlation test

The serial correlation test, also known as the autocorrelation test, measures the correlation between the current and past (lagged) observations of a stock return time series. A result of zero serial correlation indicates a lack of dependence between observations, meaning each is independent of one another. Given a covariance stationary time series r_t and k order autocorrelation coefficient denoted as $\rho(k)$, the function of serial correlation is:

$$\rho(k) = \frac{cov(r_t, r_{t-1})}{\sqrt{var(r_t)}\sqrt{var(r_{t-k})}} = \frac{cov(r_t, r_{t-k})}{var(r_t)} \tag{3}$$

Where r_t is the return at time t, k is the lag of the period. $cov(r_t, r_{t-k})$ denotes the covariance between the return at time t and its lagged return at t-k period, $var(r_t)$ is the variance on the return of time (t-1,t). For testing autocorrelation, Box and Pierce (1970) propose the portmanteau test to test jointly the several autocorrelations for r_t are zero, the function can be wrote as:

$$\rho_t = \frac{\sum_{t=k+1}^{T}(r_t - \bar{r})(r_{t-k} - \bar{r})}{\sum_{t=1}^{T}(r_{t-i} - \bar{r})^2} \tag{4}$$

Where $\bar{r}$ is the sample mean of return. Ljung and Box(1978) modify the statistic to test whether the all autocorrelations is significantly different from zero. The Q-test function is:

$$Q^* = n(n+2)\sum_{k=1}^{m}\frac{\rho^2(k)}{(n-k)} \sim \chi_m^2 \tag{5}$$

Q is asymptotically Chi-Squared distributed of m degrees of freedom. The null hypothesis is all value of $\rho(k) = 0$. If the statistics larger than the critical value and p value is less than the significant level, the null hypothesis has been rejected. Reject the null hypothesis means the process is serial correlated and the returns are not random walk. On the contrary, if null hypothesis holds, there is no significant serial correlations in the series and return follows return walk.

4.2.2 Unit root test

The augmented Dickey-Fuller (ADF) test has been used to unit root test. The test separated to three type of tests, which are “non”, “drift”, and type is “trend”. The first type “none” indicate there is no constant term and time variable in the function:

$$\Delta y_t = \gamma y_{t-1} + \varepsilon_t \tag{6}$$

Where ε_t is the error term, presumed to be white noise; $\gamma = a - 1$ from $y_t = a y_{t-1} + \varepsilon_t$; y_{t-1} refers to the previous value of y_t. The hypothesis can be denoted as:

H_0(tau1): $\gamma = 0$, the series has a unit root and it is nonstationary. It follows random walk

H_1: $\gamma \neq 0$, the series has no unit root and it is stationary

Type “drift” implies with constant but without the trend, the function is

$$\Delta y_t = a_0 + \gamma y_{t-1} + \varepsilon_t \tag{7}$$

Where a_0 is refers to drift term or constant.

H_0(tau2): $\gamma = 0$, the series has a unit root and there is no drift

H_1(phi1): $a_0 = \gamma = 0$, the series has a unit root and no drift

Rejecting the null hypothesis implies at least one of these terms(a_0 or γ) is not zero or all of them are not zero. Type “trend” tests with constant term and time trend:

$$\Delta y_t = a_0 + \gamma y_{t-1} + a_2 t + \varepsilon_t \tag{8}$$

Where $a_2 t$ is a time trend term and a_0 is drift term.

H_0 (tau3): γ = 0, the series has a unit root and it is nonstationary. It follows random walk

H_1 (phi2): $a_2 = \gamma = 0$, the series has a unit root and there is no time trend

H_1 (phi3): $a_0 = \gamma = a_2 = 0$, the series has a unit root, there is no drift and there is no trend

Rejecting this null hypothesis implies that one of a_0 , γ and a_2 or all three of these terms are not zero.

4.2.3 Runs test

The runs test can test serial independence in returns, which determines whether successive price changes are independent of each other. It is a non-parametric test, meaning it does not assume that returns are normally distributed. One run is a sequence of consecutive price changes with the same positive or negative sign or zero. To determine sign direction can be used as mean return or 0. Positive changes in returns are identified as those that are greater than the mean return or zero, while negative changes are identified as those that are less than the mean return or zero. The test compares the actual number of runs to the expected number of runs to determine if the data was generated by a random process. If data is generated by random process, actual runs (R) should close to expected number of runs (μ_R). μ_R has an approximate normal distribution for large number of runs (N> 30), so the z-statistics can be used test runs test:

$$Z = \frac{R - \mu_R}{\sigma_R} \sim N(0,1) \tag{9}$$

Where $u_R = \frac{2n_+n_-}{n} + 1$ and $\sigma_R = \sqrt{\frac{2n_+n_-(2n_+n_- - n)}{n^2(n-1)}}$

Rejecting the null hypothesis of actual runs equals expected runs means the series does not follow random walk.

4.2.4 Variance ratio test

The last traditional test was implemented in this study is variance ratio test. Variance Ratio test evaluates if the series follow a random walk by comparing the variance of sampled returns at different time intervals. It compares how the variance of the longer periods relates to the variance of the shortest period. If the stock price movements are random, the variance should grow proportionally as the periods get longer. Lo and MacKinlay (1988) mentioned this method to test the series follow random walk under both homoscedastic and heteroskedastic situation. The variance ratio test still has the assumption of returns are independently and identically distributed with a constant mean and finite variance. The equation of variance ratio test is in the following:

$$VR(q) = \frac{Var[r_t(q)]}{qVar[r_t]} \tag{10}$$

The null hypothesis of variance ratio test is VR(q) =1. Therefore, if the series follows a random walk, the variance of q period returns should be q times larger than the one-period returns. The standard normal test statistic used to derive variance ratio, Z(q) is the statistic under the null hypothesis of homoscedastic:

$$Z(q) = \frac{VR(q) - 1}{\emptyset(q)^{1/2}} \sim N(0,1) \tag{11}$$

Rejecting null hypothesis of VR(q) = 1 under this condition indicates either heteroscedasticity or the series has autocorrelation or indicate both situations exist. So null hypothesis under heteroscedastic is needed, the formular is:

$$Z^*(q) = \frac{VR(q) - 1}{\phi^*(q)^{1/2}} \sim N(0,1) \tag{12}$$

If reject the null hypothesis of VR(q) = 1, the process is autocorrelation and the series is not random walk. If VR(q) > 1, the process is positive correlated; if VR(q) <1, the process is negative correlated and we also call the process is mean-reversion.

4.2.5 Entropy Methods

The traditional methods for analyzing market efficiency are limited as they view efficiency as an all-or-none condition. However, Lo (2004) proposes that market efficiency is a continuously varying concept that changes over time rather than a constant state. In a highly uncertain environment where market participants have limited information and may behave irrationally, the market evolves dynamically according to the intrinsic rules of economic selection, forming an evolutionary system. As such, market efficiency cannot be understood as a static result from the above models alone, but must be seen as the product of the complex interplay between social, economic, political, and informational factors and the behavioral structure of market participants. To better understand the diversity of patterns and dynamical changes in a time series, entropy models and Hurst exponent can be used to measure how much a time series deviates from a completely random series.

4.2.5.1 Permutation Entropy

Given a time series $\{x(i),\ i = 1,2, \dots.\}$, with embedding dimension m and delay time L, the embedded subsequent can be constructed as:

$$X_i = [x(i), x(i + L), \dots, x(i + (m - 1)L)] \quad (13)$$

The embedding dimension m determines how much information is contained in each vector. Larger embedding dimension, less information in each sector. The next step is sort X_i in ascending order and ordinal pattern is associated:

$$[x(i + (j_1 - 1)L \ \leq \ x(i + (j_2 - 1)L \ \leq \cdots \leq x(i + (j_m - 1)L \quad (14)$$

A permutation π is created with the offset of the permuted values, $\pi = (r_0 r_1 \dots r_m)$. For example, if the time series is {7,4,9,10,6,11,3} and embedding dimension m = 3, then x(1) = {7,4,9}. After sorted the vector in ascending order, the vector x(1) = {4,7,9} and the corresponding permutation $\pi = (102)$. If two values are equal, the rank by the time of their appearance. Then mapping each vector into a new matrix by ordinal patterns. In our case, m =3, so the permuted value of m is 6 and if m =4, the permuted value is 24 different ordinal patterns. Calculating the probability of each ordinal pattern occurred in the recode matrix as P, then the PE value can be defined as

$$PE(m) = -\sum_{j=1}^{K} P_j lnP_j \tag{15}$$

A normalized permutation entropy can be defined as:

$$0 \leq PE_{norm}(m) = -\frac{PE(m)}{log_2 m!} \leq 1 \tag{16}$$

Normalized PE value is between 0 and 1. The PE value is close to 1 refer to the series contains more noisy information and hard to predict the future value.

4.2.5.2 Approximate Entropy

The approximate entropy also can quantify the complexity of a dynamic system or we can use the approximate entropy as an index of complexity for time series (Rodriguez, 2022). Higher(lower) entropy value means the series has a higher(lower) degree of uncertainty or randomness. Calculating approximate entropy must select two parameters: embedding dimension m and noise filter or similarity filter r. Same as permutation entropy, m is the length of the template and r is threshold to determine "match" if the distance of the template is less than r. The algorithm can be denoted in the following:

Given a time series of length N: $\mu = \{\mu(1), \mu(2), \dots, \mu(N\}$ with m and r, the blocks $x(i) = \{\mu(i), u(i+1), \dots, \mu(i+m-1)\}$ and $x(j) = \{\mu(j), u(j+1), \dots, \mu(j+m-1)\}$, and the distance between them can be calculate as $d[x(i), x(j)] = max_k(\mu(i+k-1) - \mu(j+k-1)|)$. For example, we have previous example's sequence {7,4,9,10,6,11,3} with m =2 and r = 3. The first block is [7,4] as the template to compare with itself and other blocks. $x(1) = d[7,4] = 5$. If x(1) value is less than or equal to 4, x(1) consider as "possible", and we can compare next position. In this case, 5 is larger than 3 so that we can stop comparison and move to next template [4,9] to find the "match" and "possible". The normalized equation can be wrote as:

$$C_i^m = \frac{d[x(i), x(j)] \leq r}{N - m + 1} \tag{17}$$

$$\phi^m(r) = \frac{1}{N - m + 1} \sum_{i=1}^{N-m+1} logC_i^m(r) \tag{18}$$

We can define $ApEn(m, r, N) = \phi^m(r) - \phi^{m+1}(r)$. According to Pincus (1994), ApEn can be used to the raw data and a greater value of ApEn also associate with non-linearity. Pincus(1994) recommend use lower m like 2 or 3 and r is in the range of 0.1 to 0.25 standard deviation of the series. But limited paper discussed the influence on different parameter inputs on testing stock market series' efficiency. The following chapter will discuss this in detail.

4.2.5.3 Sample Entropy

Sample entropy was proposed by Richman and Moorman (2000) and it is based on approximate entropy but without self-counting. In this case, sample entropy has less regularity compared to approximate entropy and also the sample entropy is more stable than approximate entropy. The function of sample entropy is represented with following equation:

$$SampEn = -\ln\left(\frac{A}{B}\right) \tag{19}$$

Where A is the sum of number of times that $d[|x_{m+1}(j) - x_{m+1}(i)|] < r$ and B is the sum of number of times that $d[|x_m(j) - x_m(i)|] < r$.

Sample entropy doesn't include (N-m) terms in its formular so that it does not depend on size of series as approximate entropy does. Same as other entropy methods, higher entropy value determines less pattern in the series and high level uncertainty.

4.2.5.4 A Simulation Approach to Measure Stock Market Efficiency by Using Entropy Methods

In this section, I designed two simulation studies to evaluate the performance of entropy models (Approximate Entropy, Sample Entropy, and Permutation Entropy) for detecting market regime change. The impact of the threshold parameters “r” and “m” on the analysis of financial data using Approximate Entropy (ApEn) and Sample Entropy (SampEn) is also discussed. The simulation models were constructed using an autoregressive (AR) model due to its foundational concept that past values influence present value. Specifically, an AR(1) model was used to investigate the correlation between present and past series.

An AR(1) process is given by:

$$X_t = c + \varphi X_{t-1} + \varepsilon_t \tag{20}$$

where ε_t is a white noise process with zero mean and constant variance σ_ϵ^2. The slope of an AR model can vary from -1 to 1, with higher values indicating greater persistence and correlation between current and previous values. By using simulation approach, it is possible to manipulate the coefficients to generate random walk series or simulate periods of high market correlation.

Simulation Model 1

The first study examines the impact of static coefficients on the simulation. The resulting series is comprised of three sub-samples with a total length of 1000, randomly divided into series 1 (length is 287), series 2 (length is 399), and series 3 (length is 314). Series 1 and 3 represents non-correlated models with a coefficient of 0.01, while series 2 represents a perfectly correlated simulation with a coefficient of 0.99. The formula used for the first simulation experiment is as follow:

$$y_t^1 = 0.01y_{t-1}, n = n_1 \tag{21}$$

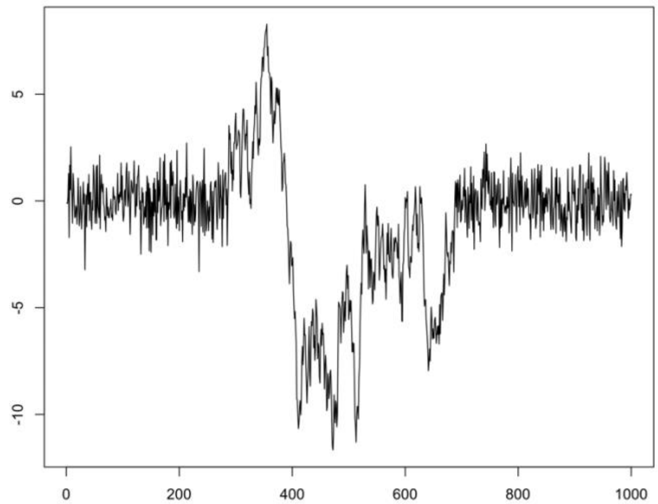
$$y_t^2 = 0.99y_{t-1}, n = n_2 \tag{12}$$

$$y_t^3 = 0.01y_{t-1}, n = n_3 \tag{23}$$

$$y_t = \{y_t^1, y_t^2, y_t^3\}, where\ n = 1000 \tag{24}$$

Figure 4. The Time Series Plots of the Simulation Experiment 1

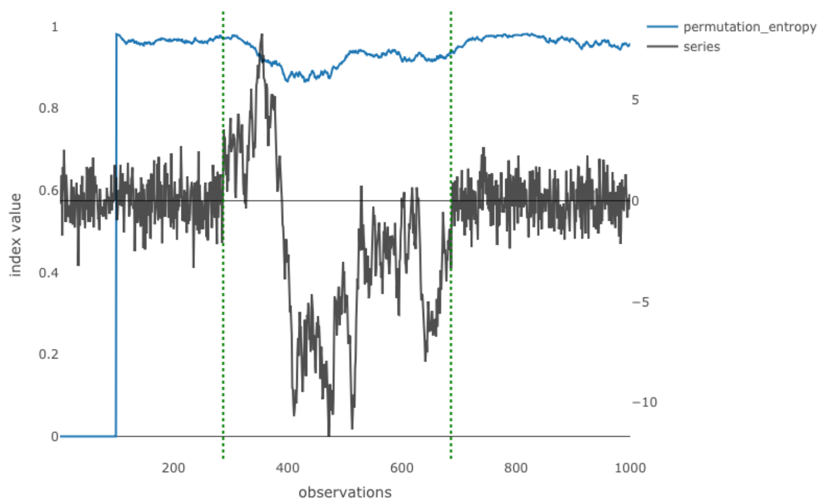
The graph shows the time series plot of the AR(1) simulation model. The data length is 1000. The first and third time series represent periods of lower correlation, while the middle window depicts a period where the current value is highly correlated with the previous value.



In order to calculate Approximate Entropy and Sample Entropy, two critical parameters must be selected: the embedding dimension "m" and the similarity tolerance or noise filter "r". To examine the impact of different parameter combinations, ApEn and SampEn were computed for m = {2,3,4} and r = {0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5} times the standard deviation of the series. The entropy results were computed using a 100 data points moving window and are presented in the following graphs:

Figure 5. Permutation Entropy Time Series V.S. Original Series

The blue line is permutation entropy result base on AR(1) process and the black line is orginal series based on equation 4. Green lines seperated three market phases.



The Permutation Entropy (PE) shows a narrow variance with an average value of 0.95 and standard deviation of 0.03 in Figure 5. It illustrates that PE decreases when the series changes from a random to highly correlated phase and increases gradually when it shifts back to randomness. Notably, the series experiences a sharp drop from data point 354 to 410, which simulates the stock market's sudden crash. PE starts to decrease in 304 data points that it advances around 40 data points when the market starts to crash and the lowest point of PE is 400, which is also 10 points earlier than the rebound point. This result follows Hou et al.'s conclusion that the PE decrease can be an early warning sign for regulators and investors to predict market crashes. However, the speed of the PE value increase is slower when the series shifts back to randomness than when the market crashes. This suggests that PE is sensitive to market crashes or bubble bursts, but not easily affected in the reverse situation. Nevertheless, the slight value variance of PE can pose challenges in accurately predicting market crashes. In our results, the PE values range from 0.98 to 0.96 when the series is random and 0.95 to 0.85 when there is a regime change or huge decrease in the series.

Figure 6. SamEn and ApEn Plots with m =2 and r = {0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5} *sd with rolling window N = 100

The following graphs from figure 6.1 to 6.9 showed the relationship among Sample Entropy, Approximate Entropy, and orginal series. The blue lines are sample entropy and the orange lines are approximate entropy with embedding dimension (m) is 2 and noise filter r equals to 0.1 to 0.5 times the standard deviation of the series respectecly.

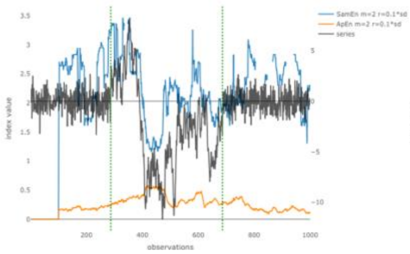


Figure 6.1

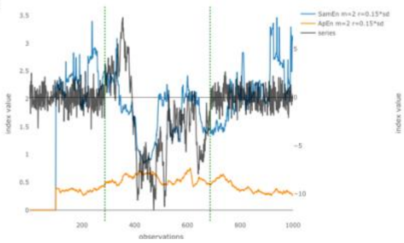


Figure 6.2

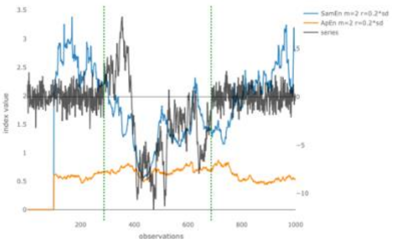


Figure 6.3

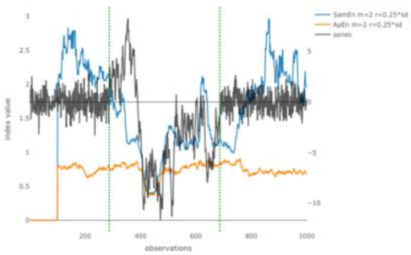


Figure 6.4

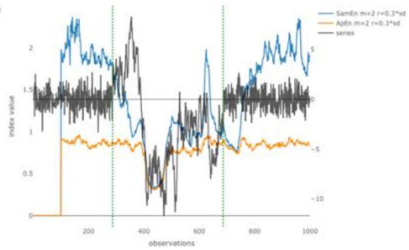


Figure 6.5

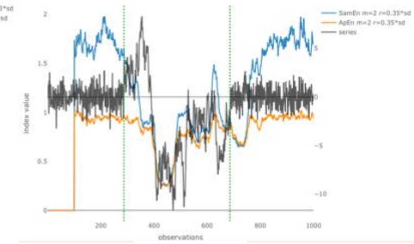


Figure 6.6

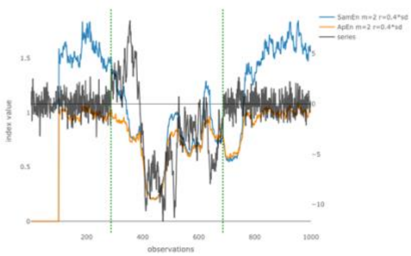


Figure 6.7

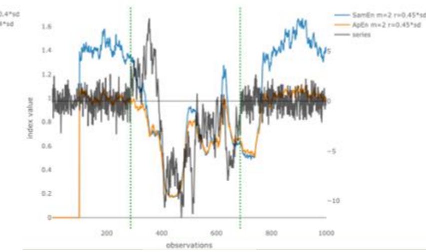


Figure 6.8

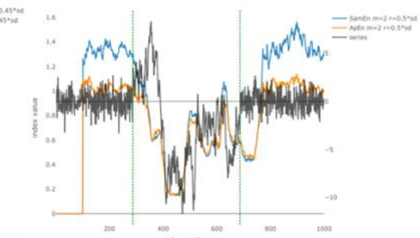


Figure 6.9

Comparing all results from figure 6, Sample Entropy values range from 0.1 to 3, while Approximate Entropy values range from 0.1 to 1, with Sample Entropy exhibiting higher variance. Both entropy methods demonstrate lower values during the highly correlated phase compared to the random phase (figure 6.3 to figure 6.9), indicating their ability to detect phase changes. Both methods can quickly identify the shift from the random phase to a more deterministic phase, with the value decreasing rapidly, although Sample Entropy exhibits a sharper decline than the Approximate Entropy method. However, neither method provides an early warning signal when the market returns to a random walk phase. For selecting the parameter r, sample entropy performs better with r $\geq 0.2 \times$ sd(ts) and approximate entropy requires a higher noise filter, with r $\geq 0.25 \times$ sd(ts). Finally, both entropy values decrease as the noise filter increases, as demonstrated in figures 6.10 and 6.11.

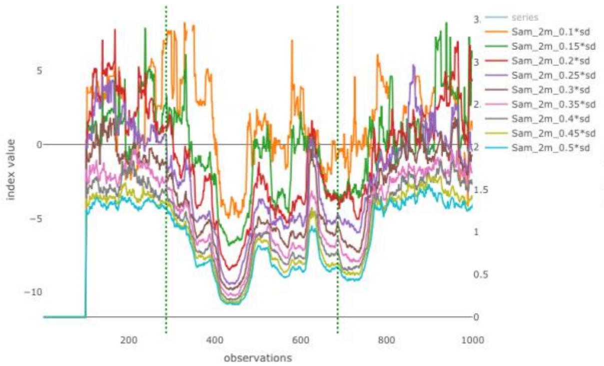


Figure 6.10 Sample Entropy plots with r from 0.1 to 0.5 *sd(ts)

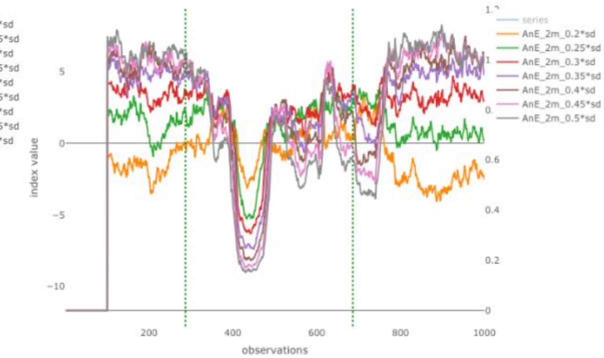


Figure 6.11 Approximate Entropy plots with r from 0.2 to 0.5 *sd(ts)

Figure 7 and Figure 8 show results for embedding dimensions 3 and 4. For m =3, Sample Entropy has similar trends as m = 2 but requires higher noise filter ($r \geq 0.35 \times sd(ts)$) to avoid missing values. Approximate Entropy cannot detect the transition from deterministic to random phase as both phases have similar ApEn values (figure 7.6 to figure 7.9), and it is slower to recognize the transition from random to deterministic phase than m =2 condition. For m = 4, sample entropy requires a higher similarity tolerance (>0.4 times standard deviation) to detect phase transitions. Approximate entropy has similar issues in detecting phase transition as m=3. Suitable parameters for sample entropy are m=2 and r={0.2,0.25}times standard deviation or m=3 and r={0.35,0.4} times standard deviation. For approximate entropy, the parameters are m=2 and r={0.3,0.35} times standard deviation. The second simulation experiment will use these parameters to ensure robustness.

Figure 7. SamEn and ApEn Plots with m =3 and r = {0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5} *sd with rolling window N = 100

The following graphs from figure 7.1 to 7.9 showed the relationship among Sample Entropy, Approximate Entropy, and original series. The blue lines are sample entropy and the orange lines are approximate entropy with embedding dimension (m) is 3 and noise filter r equals 0.1 to 0.5 times the standard deviation of the series respectecly.

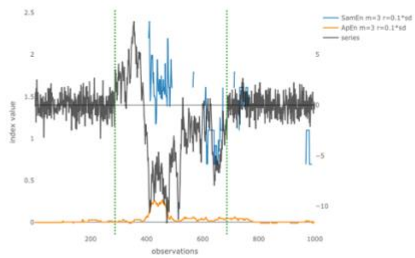


Figure 7.1

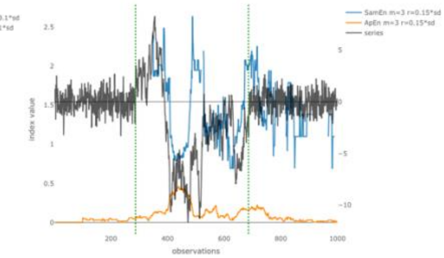


Figure 7.2

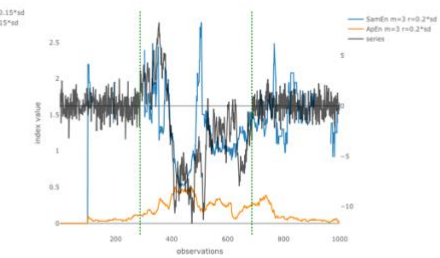


Figure 7.3

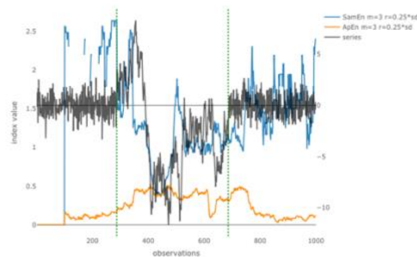


Figure 7.4

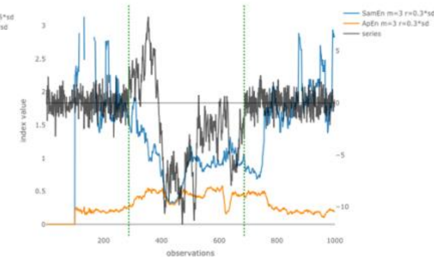


Figure 7.5

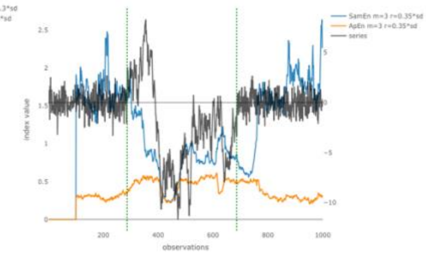


Figure 7.6

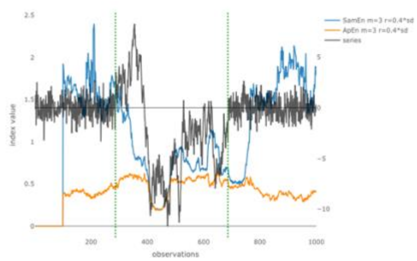


Figure 7.7

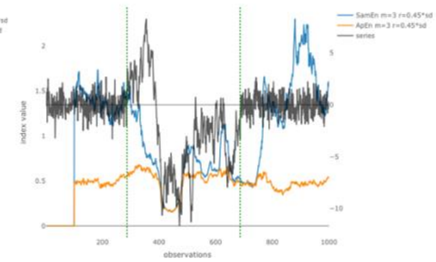


Figure 7.8

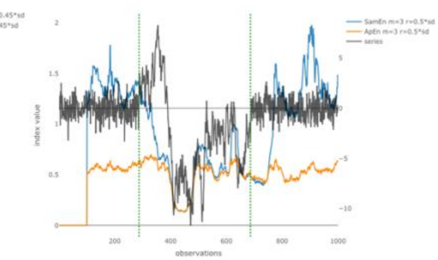


Figure 7.9

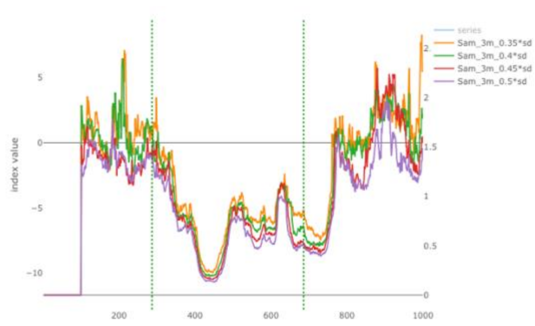


Figure 7.10 Sample Entropy plots with r from 0.35 to 0.5 *sd(ts)

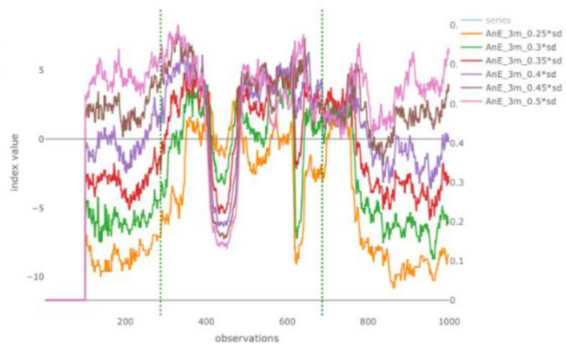


Figure 7.11 Approximate Entropy plots with r from 0.25 to 0.5 *sd(ts)

Figure 8. SamEn and ApEn Plots with m =4 and r = {0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5} *sd with rolling window N = 100

The following graphs from figure 8.1 to 8.9 showed the relationship among Sample Entropy, Approximate Entropy, and original series. The blue lines are sample entropy and the orange lines are approximate entropy with embedding dimension (m) is 4 and noise filter r equals 0.1 to 0.5 times the standard deviation of the series respectecly.

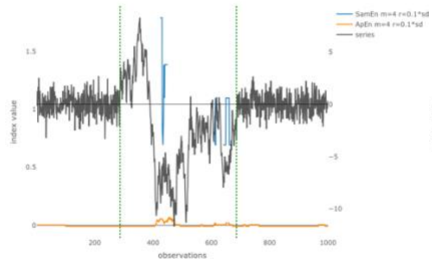


Figure 8.1

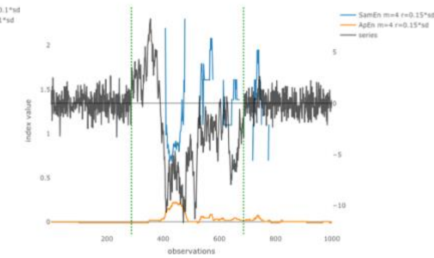


Figure 8.2

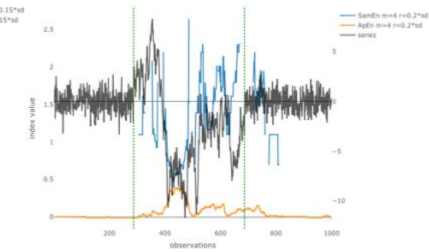


Figure 8.3

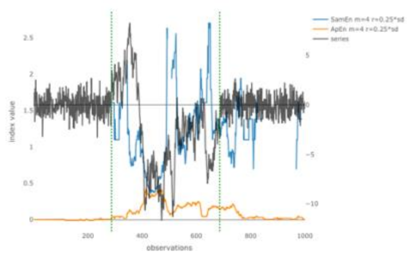


Figure 8.4

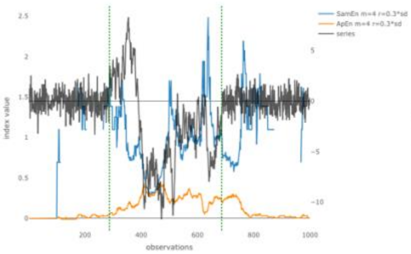


Figure 8.5

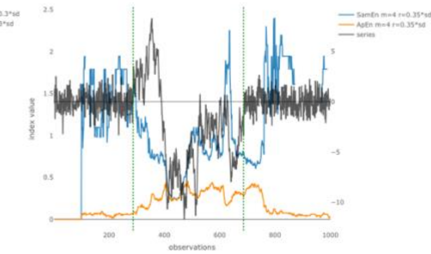


Figure 8.6

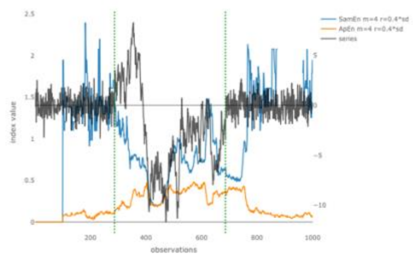


Figure 8.7

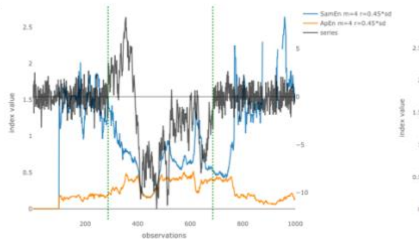


Figure 8.8

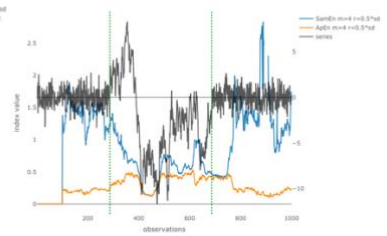


Figure 8.9

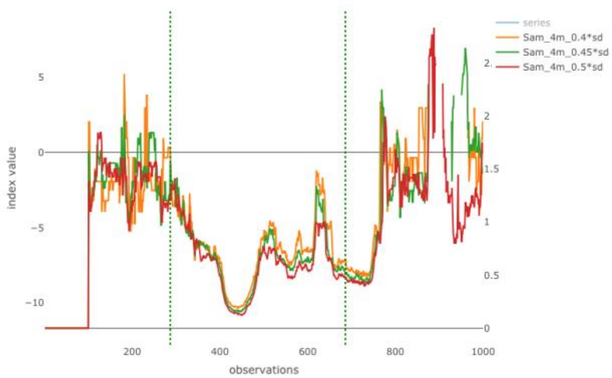


Figure 8.10 Sample Entropy plots with r from 0.4 to 0.5 *sd(ts)

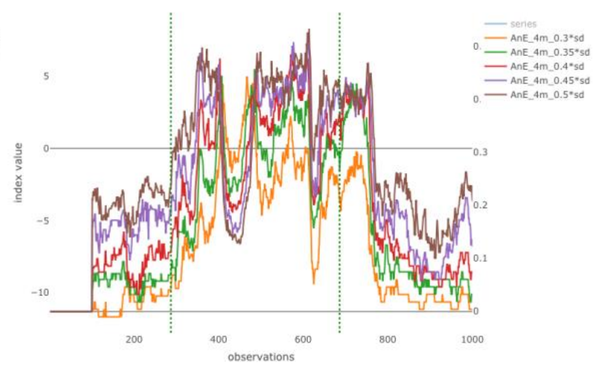


Figure 8.11 Approximate Entropy plots with r from 0.3 to 0.5 *sd(ts)

Simulation Model 2

The second study builds upon the first simulation of an AR(1) model by using a uniform distribution for the coefficient, instead of a static value. This experiment aims to verify that the entropy methods also hold in a general case. The coefficient range for series 1 and 3 is -0.5 to 0.3, representing a low correlation between the current and previous time, and the series is more random. Series 2's coefficient is a uniform distribution between 0.8 and 1. According to experiment 1's results, the suitable parameters for Sample Entropy are m = 2 and r = {0.2,0.25} times standard deviation or m =3 and r = {0.35,0.4} times standard deviation, and for Approximate Entropy, the parameters are m = 2 and r = {0.3,0.35} times standard deviation. The simulation formula for experiment 2 is as follows:

$$y_t^1 = \beta_1 y_{t-1}, n = n_{1,}\ \beta_1\ is\ uniform\ distribution\ between - 0.5\ and\ 0.3 \quad (24)$$

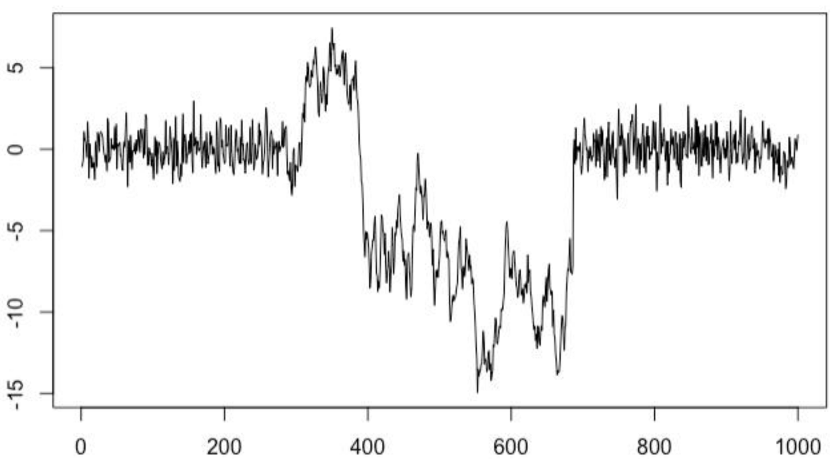
$$y_t^2 = \beta_2 y_{t-1}, n = n_{2,}\ \ \beta_2\ is\ uniform\ distribution\ between\ 0.8\ and\ 1 \quad (25)$$

$$y_t^3 = \beta_3 y_{t-1}, n = n_{3,}\ \ \beta_3\ is\ uniform\ distribution\ between - 0.5\ and\ 0.3 \quad (26)$$

$$y_t = \{y_t^1, y_t^2, y_t^3\}, where\ n = 1000 \quad (27)$$

Figure 9. The Time Series Plots of the Simulation Experiment 2

The graph shows the time series plot of AR(1) simulation model. The data length is 1000. The first and third time series represent a less correlated time period and the middle window shows current value is highly correlated with the previous value. The lengths of each series are the same as model 1, which is series 1 is 287, series 2 is 399 and series 3 is 314.



1) Rolling window length N = 100

Figure 10 displays the relationship between permutation entropy and simulated series. Permutation entropy presented a similar pattern as showed in the previous experiment. Specifically, during the transition from phase 1 to phase 2, the permutation entropy rapidly drops within the first 30 data points, indicating a shift from a random to a more deterministic series. Moreover, during phase 2, the permutation value is lower compared to other phases, suggesting that this phase is less chaotic. The permutation value is from 0.98 to 0.94 during random series phases and is from 0.93 to 0.85 in phase 2. It is worth noting that the variance of permutation entropy remains narrow throughout the analysis.

For approximate entropy and sample entropy, the selected parameters combination of embedded dimension (m) and similarity tolerance(r) showed a significant performance to detect phase changes in simulation model 2. Both entropy methods can quickly recognize phase transition from random series to less random series, and the value of phase 2 is much lower than phase 1. During more deterministic series (phase 2), the sample entropy is mostly less than 1, but it is between 4 to 1.5 when the series is random. Similarly, approximate entropy detects this pattern, although with lower variance than sample entropy. The ApEn value quickly drops from 1 to 0.3 during the phase change from 1 to 2, but it doesn't remain consistently low during phase 2. Both methods also indicate that the transition from phase 2 to phase 3 cannot be rapidly detected, which is consistent with the results from model 1. It takes around 100 data points for the value to increase, suggesting that these methods can be useful in detecting an early warning signal of a market crash, but take longer to recognize when the market has recovered and returned to a random series.

In Figure 11.3, I compare sample entropy series and approximate entropy series for different parameters combinations. I observe that as the embedded dimension values or similarity tolerance value increases, the entropy value decreases. Sample entropy exhibits more significant difference compared to approximate entropy. The performance has a similar pattern across the different parameter combinations. Thus, I recommend using m =2 and r = 0.2 *sd(ts) for sample entropy and m = 2 and r = 0.3*sd(ts) for approximate entropy in the following China's stock market efficiency testing.

Figure 10. Permutation Entropy Time Series V.S. Original Series

The blue line is the permutation entropy result based on AR(1) process, and the black line is the orginal series based on equation 8. Green lines separated three market phases.

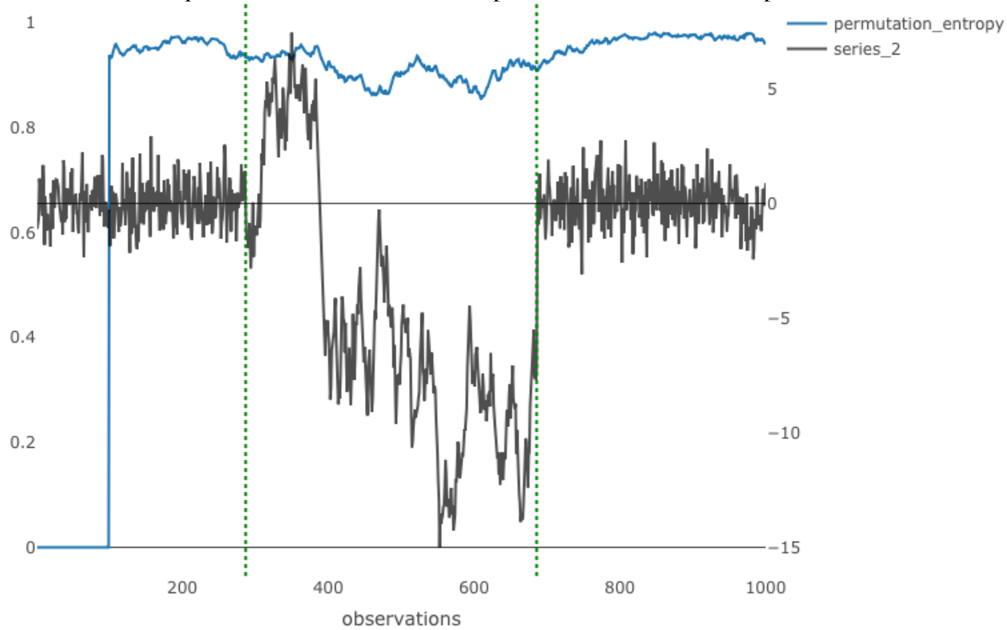


Figure 11. SamEn and ApEn Plots with rolling window N = 100

Figure 11.1 showed a sample entropy relationship with series 2 with m = 2, r = {0.2,0.25}*sd(ts) and figure 11.2 showed an approximate entropy relationship with series 2 with m =2, r = {0.3,0.35} *sd(ts).

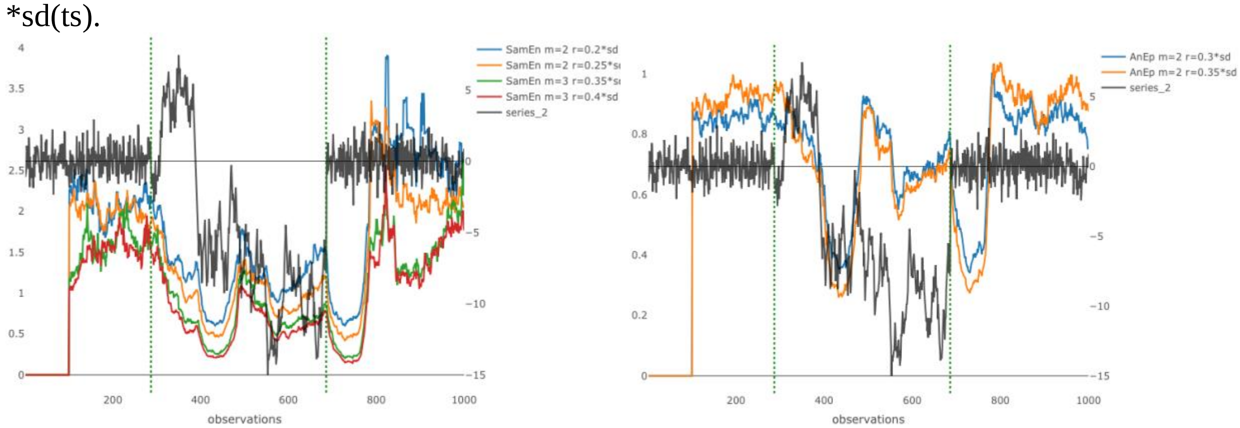


Figure 11.1 Sample Entropy plots with m=2, r ={0.2,0.25}*sd(ts) and m=3, r ={0.35,0.4}*sd(ts)

Figure 11.2 Approximate Entropy plots with m=2, r ={0.3,0.35}*sd(ts)

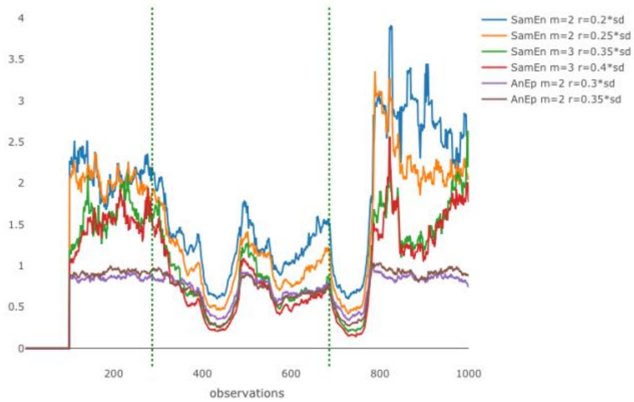


Figure 11.3 Sample Entropy and Approximate Entropy plots

2) Rolling window length N = 50 and N = 200

Since approximate entropy and sample entropy's result is also sensitive to the length of the time series (N), I employed two different rolling window lengths (N = 50 and N = 200) to calculate approximate entropy and sample entropy. The corresponding results are shown in the figures below:

Figure 12. SamEn and ApEn Plots with rolling window N = 50

Figure 12.1 showed sample entropy relationship with series 2 with m = 2, r = {0.2,0.25}*sd(ts), and figure 12.2 showed an approximate entropy relationship with series 2 with m =2, r = {0.3,0.35} *sd(ts) in rolling window length is 50.

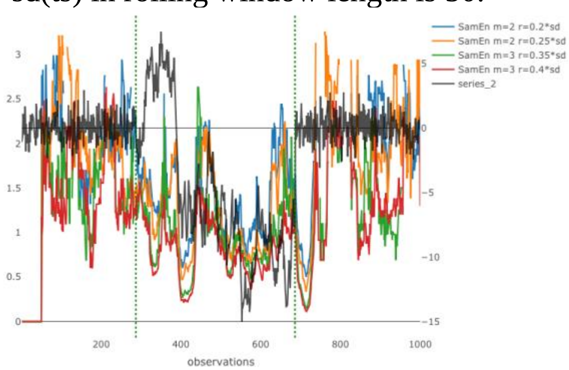


Figure 12.1 Sample Entropy with rolling window N = 50

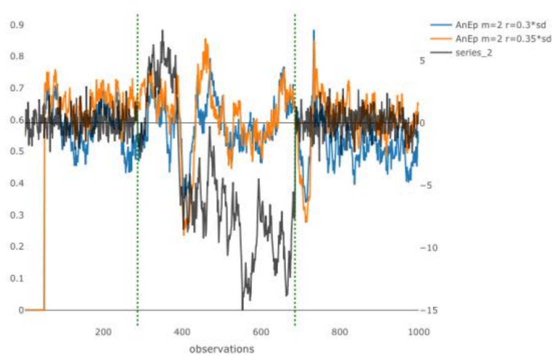


Figure 12.2 Approximate Entropy with rolling window N = 50

Figure 13. SamEn and ApEn Plots with rolling window N = 200

Figure 13.1 showed a sample entropy relationship with series 2 with m = 2, r = {0.2,0.25}*sd(ts), and figure 13.2 showed an approximate entropy relationship with series 2 with m =2, r = {0.3,0.35} *sd(ts) in rolling window length is 200.

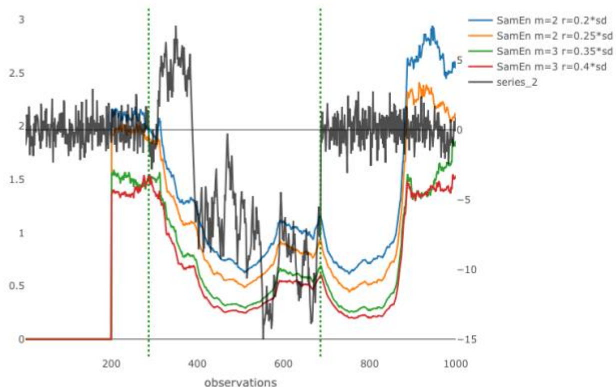


Figure 13.1 Sample Entropy with rolling window N = 200

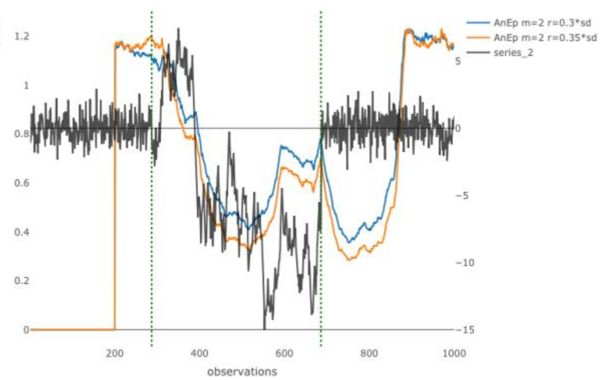


Figure 13.2 Approximate Entropy with rolling window N = 200

Figure 12 indicates the rolling window length is 50 and figure 13 shows the length is 200. Comparing two results, the rolling window length of N = 200 is better than N = 50. When the rolling window length is 50, the results become too noisy to detect phase changes accurately, especially for approximate entropy. During phase 2, the approximate entropy value cannot differentiate from other phases. The results obtained with a rolling window length of 200 exhibit a similar pattern to those with a length of 100. However, because the entropy methods take longer to detect the transition from a less random to a random phase, rolling window 200 creates longer lags than rolling window 100. Additionally, longer rolling windows may cause some important information to be lost. Therefore, in subsequent empirical studies, I will employ a half-year rolling window (N= 126) to test China's stock market efficiency.

4.2.6 Hurst Exponent

Hurst exponent used to measure long-term memory in the series that the method can be implied to test the weak-form efficiency. This method also quantifies the level of randomness and can tell the price changes pattern. In this study, I used rescaled range (R/S) Hurst analysis to test Hurst exponent. The process can be summarized in the following:

- Calculating mean of the series $\{x_t\}$ by $\mu = \frac{1}{n}\sum_{t=1}^{n} x_t$
- Generating a new series $\{y_t\}$ by $y_t = x_t - \mu$

- The adjusted range is calculated as

$$R_n = [max \sum_{j=1}^{k}(y_j - \bar{y}) - min \sum_{j=1}^{k}(y_j - \bar{y}) \quad (28)$$

- R/S can be wrote as $\frac{R_n}{S_n} = cn^H$, where s is the estimated standard deviation of the sample, c is constant, and H is the Hurst exponent. We can take log of each side, then the function is

$$\log\left(\frac{R}{S}\right) = \log(c) + Hlog(n) \quad (29)$$

Where H is the estimate slope.

If H > 0.5, the time series is persistent (positive correlation). If 0<H<0.5, the time series is anti-persistent (negative correlation). H=0.5, there is no correlation or at most short-range correlation in the time series. As the frequency of similar price change patterns increases, the Hurst exponent has a higher value, H > 0.5. That is, as the degree of efficiency decreases, the Hurst exponent will become greater.

Chapter 5 Empirical Results

5.1 Analysis of Descriptive Statistics

An overview of descriptive statistics for prices and returns of the Shanghai composite index and Shenzhen component index from 1990 to 2021 are displayed in Tables 1a and 1b. In table 1a, sub-sample 5 stands out with the highest average value of 3106.26, indicating a momentum trend for the mean of the index's price to increase. The two boom-bust periods show higher standard deviations than other periods, suggesting greater volatility during those times. The highest index price recorded was 6092.06 during the first boom and bust period. Normally, the normal distribution's skewness is 0 and kurtosis is 3. However, sub-samples 1 and 5 are skewed to the left, while the entire period, sub-sample 2, 3, and 4 are skewed to the right. Kurtosis of all periods is less than 3. Therefore, the entire period of SSEC's price and the five sub-samples are not normally distributed. The Jarque-Bera test confirms this conclusion, with p-values for all samples being less than 0.0001 and rejecting the null hypothesis

As for the statistics' result of return series, mean is approach to 0 and the standard deviation range is from 0.01 to 0.03. The first period (sub-sample 1) shows larger returns than the other periods since the stock market was more volatile during its early stage. The skewness of the entire period's return is 5.35, while the kurtosis value is 161.43, indicating a more peaked and skewed right distribution of returns during the entire period. Except for the first period, the returns for the other 4 sub-samples are negatively skewed, suggesting a higher likelihood of significant declines in returns than increase. The second boom-bust period (period 4) has the highest negative skewness value, while the first boom-bust period (period 2) has the lowest. For Kurtosis, except for the first-period value, which has a value of 140.05, the other four periods have values ranging from 2.23 to 6.18. The period 2 and 3's kurtosis value is close to 3, with values of 2.58 and 2.23 respectively. Periods 4 and 5 have kurtosis values larger than 3, indicating leptokurtic distributions and fatter tails than other periods. The p-values of the Jarque-Bera test for all periods are less than 0.001 level of significance, indicating the rejection of the null hypothesis of the normal distribution. Therefore, none of these periods' returns follow a normally distributed.

Table 1b presents the descriptive statistics for the Shenzhen component index (SZSE). The sample period for SZSE starts on January 24, 1995, and the total points amount to 6418, with a base date of July 20, 1994. The average price of SZSE exhibits a momentum trend to rise, moving from 3331.11 points to 10827.15 over the different periods. Similar to the Shanghai composite index, the mean return of SZSE is positive and approximately zero. All periods' standard deviation of returns is 0.02, except for the last period is 0.01. SZSE's returns also show negative skewness in all periods, except the first period, which has positive skewness and follows a leptokurtic distribution with a kurtosis is 13.1. Period 4 has the highest skewness of -0.96, while period 3 has the lowest of -0.29. The kurtosis values of periods 2, 3 and 4 are less than 3 (1.38, 1.87 and 2.5, respectively), indicating a platykurtic distribution with a lower peak and thinner tails. Period 5 has a kurtosis of 3.69 kurtosis. In line with the findings for SSEC, all p-values of the Jarque-Bera test for SZSE are less than 0.0001 level, rejecting the null hypothesis and indicating that none of the periods' returns are normally distributed. Compared to the Shenzhen market, the Shanghai market follows leptokurtic distribution and shows a fat tailer, indicating Shanghai markets will experience more occasional extreme returns.

Table 1.a Shanghai Composite Index (SSEC) Price and Returns Descriptive Table of Boom-and-Bust Periods

The table displays descriptive statistics of the Shanghai Composite Index's price and returns for the first boom-and-bust investigation. The table includes the number of observations, mean, standard deviation, maximum, minimum, range, skewness, kurtosis, and Jarque-Bera. The bull-and-bust period is highlighted in red color.

	whole sample	sub-sample1	sub-sample2	sub-sample3	sub-sample4	sub-sample5
date	1990-12-20 to 2021-07-07	1990-12-20 to 2004-12-31	2005-01-04 to 2009-01-05	2009-01-06 to 2014-03-31	2014-04-01 to 2016-06-01	2016-06-02 to 2021-07-07
period	whole period	regular	boom-bust	regular	boom-bust	regular
obs.	7465	3451	973	1269	532	1240
			Price			
mean	2015.62	1137.47	2514.35	2514.58	3067.51	3106.26
sd	1083.05	526.09	1414.07	378.39	759.74	263.52
min	104.39	104.39	1011.5	1863.37	2003.49	2464.36
max	6092.06	2242.42	6092.06	3471.44	5166.35	3696.17
range	5987.67	2138.03	5080.56	1608.07	3162.86	1231.81
skew	0.47	-0.12	0.82	0.42	0.51	-0.17
kurtosis	-0.02	-0.74	-0.6	-1	-0.25	-0.65
Jarque-Bera	269.46	85.955	122.35	88.849	24.638	27.664

Jarque-Bera (P-value)	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001
Returns						
mean	0	0	0	0	0	0
sd	0.02	0.03	0.02	0.01	0.02	0.01
min	-0.18	-0.18	-0.09	-0.07	-0.09	-0.08
max	0.72	0.72	0.09	0.06	0.06	0.06
range	0.9	0.9	0.18	0.13	0.14	0.14
skew	5.35	5.98	-0.28	-0.37	-1.15	-0.63
kurtosis	161.43	140.05	2.58	2.23	3.79	6.18
Jarque-Bera	8145984	2844454	284.54	293.33	439.7	2067.9
Jarque-Bera (P-value)	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001

Table 1.b Shenzhen Component Index (SZSE) Price and Returns Descriptive Table of Boom-and-Bust Periods

The table displays descriptive statistics of the Shenzhen Component Index's price and returns for the first boom-and-bust investigation. The table includes the number of observations, mean, standard deviation, maximum, minimum, range, skewness, kurtosis, and Jarque-Bera. The bull-and-bust period is highlighted in red color.

	whole sample	sub-sample1	sub-sample2	sub-sample3	sub-sample4	sub-sample5
date	1995-01-24 to 2021-07-07	1995-01-24 to 2005-12-30	2006-01-04 to 2009-01-05	2009-01-06 to 2014-03-31	2014-04-01 to 2016-06-01	2016-06-02 to 2021-07-07
period	whole period	regular	boom-bust	regular	boom-bust	regular
obs.	6418	2647	731	1268	532	1240
Price						
mean	7450.19	3331.11	9427.08	10293.39	10580.77	10827.15
sd	4157.53	1055.24	5022.99	1833.07	2539.98	1905.27
min	930.06	930.06	2948.8	6530.81	7151.18	7089.44
max	19531.15	6019.23	19531.15	14051.52	18098.27	15962.25
range	18601.09	5089.17	16582.35	7520.71	10947.09	8872.81
skew	0.33	-0.64	0.46	0.18	0.63	0.62
kurtosis	-0.88	0.08	-1.14	-1.13	-0.01	-0.05
Jarque-Bera	326.99	180.62	64.508	74.288	35.466	80.448

Jarque-Bera (P-value)	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001
Returns						
mean	0	0	0	0	0	0
sd	0.02	0.02	0.02	0.02	0.02	0.01
min	-0.18	-0.18	-0.1	-0.08	-0.09	-0.09
max	0.21	0.21	0.09	0.07	0.06	0.05
range	0.39	0.39	0.19	0.15	0.15	0.14
skew	-0.21	0.26	-0.41	-0.29	-0.96	-0.66
kurtosis	7.46	13.19	1.38	1.87	2.5	3.69
Jarque-Bera	14946	19249	79.604	203.36	222.46	797.5
Jarque-Bera (P-value)	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001

5.2 Serial Correlation Test

Serial correlation measures the correlation between the current and lagged observation of a time series of stock returns. A value of 0 for serial correlation indicates no correlation, whereas a positive value indicates that future values are likely to change in the same direction as the current values. Conversely, a negative value suggests that future values are likely to move in the opposite direction of the current values. The Ljung-Box test is commonly used to test serial correlation. If the null hypothesis is rejected, it indicates that the series is not independently distributed, and future observations are influenced by past values.

H_0: *the residuals are independently distributed*

H_1: *the residuals are not independently distributed and exhibit serial correealtion, not random*

Table 2a and 2b present the results of Ljung-Box statistics for lag 1, lag 2, lag 5, lag 10, and lag 30 for each return series of SSEC and SZSE for the entire sample and each sub-sample. SSEC includes a sub-sample 1-1 from the same start date as the Shenzhen market, spanning from 1995-01-24 to 2005-12-30. The results show that for both markets and all lag lengths, the autocorrelation coefficients are rejected by LB-statistics at a 1% level and the coefficients are positive except for the autocorrelation coefficients of lag 2 on the Shenzhen market, which are negative. This result is consistent with previous findings in China’s stock market and emerging markets autocorrelation test, such as Chung (2006), Hassan et al. (2006), Mobarek and Keasey(2002), Lim(2009), and Hamid et al.(2017). Most papers discovered significant serial correlation in the returns of emerging markets and China’s stock market. The autocorrelation of daily returns of both markets decays gradually as the lag length increases, which is similar to the findings of Ma and Barnes (2001).

Before the 2008 Global Financial Crisis, the autocorrelation coefficients for SSEC in lag1 to lag30 were rejected by LB- statistics at 1% level of significance and the coefficients are positive, indicating that future returns were likely to change in the same way as historical returns over a period of at least 30 days in the Shanghai market. However, during the boom-and-bust period from 2006 to 2009, the autocorrelation coefficients of lag 1, lag2, and lag 10 were accepted at the null hypothesis of residual are independently distributed, while lag 5 and lag 30 were rejected at a 10% and 1 % level of significance, respectively. On the other hand, sub-sample 3's LB-statistics test for lag1, lag2, lag5, and lag10 could not reject the null hypothesis except for lag30, indicating that the returns series during this period followed a random walk and were not correlated with previous days in the short term. During the second bull-and-bust period (sub-sample 4) from 2014 to 2016, the autocorrelation coefficients of lag1 were rejected LB-statistics at a 10% level of significance and lag5 to lag30 are rejected at a 1% level of significance, while lag2 can not reject. For the last sub-sample (2016 to 2021), the LB-statistics show that the null hypothesis of no autocorrelation was accepted for the returns at lag1 and lag2. Other lags were rejected at a 5% level of significance for lag5 and lag10 and at a 1% level for lag30. In conclusion, the results indicate that the returns of the Shanghai market are not correlated with previous returns in the short-term (1 to 10 days lag) after the boom-and-bust period. However, the returns still tend to follow the previous data for a longer period in the same direction in most periods. If we consider sub-sample 2 and 4 periods are outliers of the whole sample series or we want to discard the noise of boom-and-bust periods, the results suggest that the Shanghai market is becoming more efficient in a shorter period.

The Shenzhen market exhibits similar patterns to SSEC. The returns of the entire sample period (1995 to 2021) rejected the null hypothesis, indicating the returns of the Shenzhen market are serially correlated and did not follow a random walk. In the sub-sample 1 period, the returns of SZSE were serially correlated in all lags except lag 10. However, when compared to SSEC's sub-sample 1-1 period, we observe that SSEC's returns are not serially correlated in lag 2, lag 5 and lag 10, which the LB-statistics cannot reject at lag1 and lag30 and the residuals are independently distributed in lag 1 and lag 30. During the first boom-and-bust period, the LB-statistics cannot reject the returns series at lag1 and lag2, while the autocorrelation of other lags is rejected at 1% or 5% level of significance. In sub-sample period 3, the LB-statistics reject lag1 at a 5% level of significance, but the null hypothesis is accepted for other lags, indicating that the returns show serial correlation. This result has a slight difference compared to SSEC sub-sample 3 period result. The returns in the Shenzhen market are more correlated with longer period historical returns, whereas in the Shanghai market, the returns are more correlated with shorter period historical returns. Sub-sample 4 period's test results for SZSE are similar to the Shanghai market, as most of lags' autocorrelation coefficients are rejected LB-statistics in 1% level of significant, except for lag 2, which shows serial correlation with returns. During the last sub-sample, all lags' autocorrelation coefficients accept the null hypothesis, and the returns exhibit no serial correlation.

Overall, if we do not consider the boom-and-bust period in Shenzhen market, it appears to be getting more efficient in all periods. During the two boom-and-bust periods, the autocorrelations of two markets' returns have similar pattern. The returns have no serial correlation in shorter period, like lag1 and lag2, but show serial correlation in longer period (lag5, lag10 and lag30). Additionally, the autocorrelation coefficient changes from positive correlation in other periods to negative correlation during the boom-and-bust period, which could indicate that investors follow the opposite direction with previous data during boom-and-bust period while following the same direction in normal periods.

Table 2a. Results of Ljung-Box test for Shanghai Index's the Full Sample Period and All Sub-Sample Period

This table provides the results of the Ljung-Box statistics in lag1, lag2, lag5, lag10, and lag30 of the daily returns on the SSEC for the full sample period from 1990 to 2021 and also each 5 sub-sample periods. The bull-and-bust period is highlighted in red color.

	Shanghai Index (SSEC)						
	whole sample	sub-sample 1	sub-sample 1-1	**sub-sample 2**	sub-sample 3	**sub-sample 4**	sub-sample 5
	1990-12-20 to 2021-07-07	1990-12-20 to 2005-12-30	1995-01-24 to 2005-12-30	2006-01-04 to 2009-01-05	2009-01-06 to 2014-03-31	2014-04-01 to 2016-06-01	2016-06-02 to 2021-07-07
period	Full period	regular	regular	bull and bust period	regular	bull and bust period	regular
lag1	0.047***	0.056***	0.036*	**-0.004**	**0.016**	0.075*	**0.003**
	(<0.00)	(0.00072)	(0.076)	(0.906)	(0.5633)	(0.0826)	(0.9189)
lag2	0.033***	0.052***	-0.01	**-0.022**	**-0.004**	**-0.051**	**0.013**
	(<0.00)	(<0.00)	(0.186)	(0.831)	(0.8395)	(0.1114)	(0.8987)
lag5	0.024***	0.032***	-0.008	0.007*	**0.004**	0.006***	-0.027**
	(<0.00)	(<0.00)	(0.4601)	(0.0783)	(0.9392)	(0.0063)	(0.02399)
lag10	0***	0.001***	0.003	**0.009**	**0.039**	-0.110***	0.030**
	(<0.00)	(<0.00)	(0.4325)	(0.115)	(0.7178)	(0.00027)	(0.03489)
lag30	0.01***	0.017***	0***	-0.016***	0.014*	-0.072***	0.056*
	(<0.00)	(<0.00)	(<0.00)	(0.0038)	(0.07272)	(<0.00)	(0.0919)

*** p<0.01, ** p<0.05, * p<0.1

Table 2b. Results of Ljung-Box test for Shenzhen Index's the Full Sample Period and All Sub-Sample Period

This table provides the results of the Ljung-Box statistics in lag1, lag2, lag5, lag10, and lag30 of the daily returns on the SZSE for the full sample period from 1995 to 2021 and also each 5 sub-sample periods. The bull-and-bust period is highlighted in red color.

	Shenzhen Index (SZSE)					
	whole sample	sub-sample 1	**sub-sample 2**	sub-sample 3	**sub-sample 4**	sub-sample 5
	1995-01-24 to 2021-07-07	1995-01-24 to 2005-12-30	2006-01-04 to 2009-01-05	2009-01-06 to 2014-03-31	2014-04-01 to 2016-06-01	2016-06-02 to 2021-07-07
period	Full period	regular	bull and bust period	regular	bull and bust period	regular
lag1	0.044***	0.042**	**0.043**	0.038**	0.089**	**0.005**
	(0.00045)	(0.029)	(0.2474)	(0.1806)	(0.038)	(0.8473)
lag2	-0.008***	0.016*	**-0.052**	**-0.015**	**-0.015**	**-0.007**
	(0.0017)	(0.066)	(0.1912)	(0.3519)	(0.1113)	(0.953)
lag5	0.006***	0.018*	-0.009***	**-0.004**	0.008*	**0.002**
	(0.00011)	(0.092)	(0.0085)	(0.5921)	(0.084)	(0.3604)
lag10	0.004***	**0.027**	0.022**	**0.033**	-0.167***	**0.029**
	(<0.00)	(0.1179)	(0.0229)	(0.2615)	(0.00)	(0.6181)
lag30	0.006***	0.007**	-0.017***	**0.010**	-0.011***	**0.057**
	(0.00022)	(0.013)	(0.0026)	(0.4259)	(0.00)	(0.4259)

*** p<0.01, ** p<0.05, * p<0.1

5.3 Unit root test

The Augmented Dickey-Fuller (ADF) test is commonly used to evaluate the null hypothesis that log price and returns follow a random walk. To determine whether to reject the null hypothesis, we compare the test statistic to the critical value in absolute terms. Table 3a and 3b show the results of the ADF test for SSEC and SZSE, respectively. The tables contain the test results of type none, drift and trend according to the equation (6), (7) and (8) for both the full period and each of the 5 sub-sample periods. In order to make SSEC comparable with SZSE's time range, sub-sample 1-1 from 1995 to 2005 is also included in the analysis unit root test of SSEC.

Table 3a. Results of the Augmented Dickey-Fuller Unit Root Test for SSEC Index Price and Returns

This table reports the results of the ADF unit root test to log prices of the Shanghai Composite Index and the first difference of price (return). The test time series include the full period and the other 5 sub-sample periods. The results displayed as without drift and time trend, with drift but without time trend, and with drift and time trend.

Shanghai Index (SSEC) Log-Price							
	whole sample	sub-sample 1	sub-sample 1-1	**sub-sample 2**	sub-sample 3	**sub-sample 4**	sub-sample 5
	1990-12-20 to 2021-07-07	1990-12-20 to 2005-12-30	1995-01-24 to 2005-12-30	2006-01-04 to 2009-01-05	2009-01-06 to 2014-03-31	2014-04-01 to 2016-06-01	2016-06-02 to 2021-07-07
period	Full period	regular	regular	bull and bust period	regular	bull and bust period	regular
None	1.36	1.09	0.74	0.56	0.08	0.64	0.49
Intercept	-3.73***	-3.27**	-2.36*	-0.99	-1.85	-1.57	-1.91
	8.46***	6.35**	3.15*	0.69	1.71	1.47	1.97
Intercept and Trend	-4.09***	-2.85	-1.82	0.55	-4.17***	-0.97	-1.99
	7.50***	4.58*	2.13	1.37	6.69***	1.09	1.47
	9.75***	5.87*	2.83	1.86	10.04***	1.39	2.08
Shanghai Index (SSEC) Return (first difference)							
None	-57.78***	-38.34***	-34.42***	-22.48***	-25.04***	-16.51***	-24.50***
Intercept	-57.81***	-38.37***	-34.43***	-22.49***	-25.03***	-16.51***	-24.50***
	1671.2***	736.08***	592.78***	252.81***	313.29***	136.35***	300.15***
Intercept and Trend	-57.84***	-38.42***	-34.48***	-22.6***	-25.10***	-16.59***	-24.49***
	1115.3***	492.13***	396.23***	170.18***	209.99***	91.79***	200.02***
	1672.9***	738.19***	594.34***	255.28***	314.99***	137.68***	3000.0***

*** p<0.01, ** p<0.05, * p<0.1

Table 3b. Results of the Augmented Dickey-Fuller Unit Root Test for SZSE Index Price and Returns

This table reports the results of the ADF unit root test to log prices of the Shenzhen Component Index and the first difference of price (return). The test time series include the full period and the other 5 sub-sample periods. The results displayed as without drift and time trend, with drift but without time trend, and with drift and time trend.

Shenzhen Index (SZSE) Log-Price						
	whole sample	sub-sample 1	**sub-sample 2**	sub-sample 3	**sub-sample 4**	sub-sample 5
	1995-01-24 to 2021-07-07	1995-01-24 to 2005-12-30	2006-01-04 to 2009-01-05	2009-01-06 to 2014-03-31	2014-04-01 to 2016-06-01	2016-06-02 to 2021-07-07
period	Full period	regular	bull and bust period	regular	bull and bust period	regular
None	1.46	0.76	1.01	0.07	0.54	0.74
Intercept	-2.08	-2.33	-1.78	-1.94	-1.64	-0.75
	3.49	3.09	2.22	1.89	1.51	0.566

Intercept and Trend	-2.38	-1.75	0.09	-4.07***	-1.27	-1.39
	3	2.36	3.40	7.08***	1.02	1.22
	3.18	3.15	4.46	10.61***	1.36	1.55
Shanghai Index (SSEC) Return (first difference)						
None	-55.88***	-35.04***	-19.68***	-25.07***	-15.84***	-224.94***
Intercept	-55.92***	-35.05***	-19.72***	-25.06***	-15.84***	-24.95***
	1563.2***	614.34***	194.53***	314.09***	125.53	311.18***
Intercept and Trend	-55.92***	-35.11***	-20.10***	-25.19***	-15.88***	-24.97***
	1042.34***	410.94***	134.69***	2111.60***	84.11***	207.88***
	1563.51***	616.41***	202.05***	317.41***	126.16***	311.83***

*** p<0.01, ** p<0.05, * p<0.1

The results presented in table 3a and 3b indicate that the null hypothesis of levels is not rejected in both markets, implying that the log price series is nonstationary. However, the returns series is stationary in all periods for both markets, as evidenced by rejecting the null hypothesis of a unit root test at a 1% level of significance. These findings are consistent with previous research by Gujarati and Porter (2009) and Guney (2022), which suggests that the first difference of a random walk series is stationary and supports the view that returns of log price are stationary.

The price series of SSEC in the whole period and sub-sample 1 have drift term and sub-sample 3 may has drift or trend term. For the Shenzhen market, except sub-sample 3 may has drift or trend term, all periods' price series do not include drift or trend. Based on log price results, these results are mixed, some early periods weakly reject random walk while others don't. Thus, based on the ADF tests, I don't find strong evidence of weak form of EMH for most of the subperiods.

5.4 Runs test

Tables 4a and 4b present the results of the runs test for SSEC and SZSE, respectively. The null hypothesis of randomness is rejected if p-value is less than the significance level. In the case of SSEC, the runs test results for the whole period and the first period (sub-sample 1) reject the null hypothesis at 1% level of significance. This indicates that the returns for the whole period of the Shanghai market, as well as the early stage, do not follow a random walk and the returns are predictable. However, when the first five years are removed from SSEC, the sub-sample 1-1 period from 1995 to 2005 becomes random, as evidenced by the runs test results that fail to reject the null hypothesis. Other sub-sample periods of SSEC fail to reject the null hypothesis of the runs test, meaning sub-sample periods of SSEC do follow a random walk but the whole period doesn't. In contrast, the Shenzhen market's returns are consistently random across all periods, with the runs test failing to reject the null hypothesis of randomness. The negative Z-values for returns suggest that the actual number of runs is less than the expected number of runs. Overall, the runs test results suggest that the Shenzhen market is generally more random than the Shanghai market, but each period's returns remain random for both markets. However, it is still challenging to determine the level of randomness of each period and the efficiency of China's stock market.

Table 4a. Results of Runs Test for Shanghai Composite Index

The table shows the results of the runs tests for SSEC in the whole period and each 5 sub-sample periods. This runs test used 0 as a threshold to calculate the days over or below 0. Total cases refer to the observations of each period and the number of runs sums up the positive runs and negative runs.

	Shanghai Composite Index (SSEC)						
	whole sample	sub-sample 1	sub-sample 1-1	**sub-sample 2**	sub-sample 3	**sub-sample 4**	sub-sample 5
	1990-12-20 to 2021-07-07	1990-12-20 to 2004-12-31	1995-01-24 to 2005-12-30	2005-01-04 to 2009-01-05	2009-01-06 to 2014-03-31	2014-04-01 to 2016-06-01	2016-06-02 to 2021-07-07
period	full period	regular	regular	bull and bust period	regular	bull and bust period	regular
Total Cases	7464	3450	2410	972	1268	532	1240
Cases < 0	3521	1667	1183	435	611	230	578
Cases >= 0	3943	1783	1227	537	657	302	662
No of Runs	3617	1602	1205	474	636	272	635
Z	-2.417**	4.161***	-0.0244	-0.496	0.103	0.873	0.962
P-value	0.0156	<0.00	0.981	0.6196	0.9178	0.3827	0.3363

*** p<0.01, ** p<0.05, * p<0.1

Table 4a. Results of Runs Test for Shenzhen Component Index

The table shows the results of the runs tests for SZSE in the whole period and each 5 sub-sample periods. This runs test used 0 as a threshold to calculate the days over or below 0. Total cases refer to the observations of each period and the number of runs sums up the positive runs and negative runs.

	Shenzhen Component Index (SZSE)					
	whole sample	sub-sample 1	**sub-sample 2**	sub-sample 3	**sub-sample 4**	sub-sample 5
	1995-01-24 to 2021-07-07	1995-01-24 to 2005-12-30	2006-01-04 to 2009-01-05	2009-01-06 to 2014-03-31	2014-04-01 to 2016-06-01	2016-06-02 to 2021-07-07
Period	Full period	regular	bull and bust period	regular	bull and bust period	regular
Total Cases	6413	2643	730	1268	532	1240
Cases < 0	3112	1330	320	633	239	590
Cases >= 0	3301	1313	410	635	293	650
No. of Runs	3201	1326	341	625	275	637
Z	-0.0929	0.138	-1.46	-0.56	0.942	0.994
P-value	0.926	0.89	0.1434	0.574	0.346	0.3203

*** p<0.01, ** p<0.05, * p<0.1

5.5 Variance ratio test

Table 5a and 5b demonstrate the variance ratio test statistics of the random walk hypothesis for the SSEC and SZSE based on the methodology of Lo and Mackinlay's variance ratio test (1988) and Chow and Denning variance ratio test (1993). The results in Table 5a suggest that the null hypothesis of random walk is rejected for all the statistics of Z(q) and Z*(q) for the full period of SSEC, implying that the SSEC does not follow a random walk under both homoscedasticity and heteroscedasticity. Similarly, the first sub-sample period from 1990 to 2005 also rejects the null hypothesis and suggests that the first period is not random. However, for sub-period 1-1, 2, 3, 4, and 5, all statistics of Z(q) and Z*(q) fail to reject the null hypothesis, indicating that these sub-samples follow a random walk. The results of the whole period and the first sub-sample period show positive returns autocorrelation, as the variance ratio value is greater than 1 (VR(q) > 1). This is consistent with the findings in the serial correlation test (Section 6.1.2)

In the case of SZSE, the results of Z(q) and Z*(q) statistics indicate that the random walk hypothesis is rejected for the full period, meaning that the return series of SZSE does not follow a random walk pattern. The variance ratio values for all lags are also larger than 1 in full period, which suggest that the return series of SZSE has positive autocorrelation. Z(q) statistics of the first period reject the null hypothesis at a 5% or 1% level of significance, but Z*(q) statistics do not reject the random walk hypothesis, indicating that the first period of SZSE follows a heteroscedasticity random walk pattern but not a homoscedasticity random walk pattern. Comparing the same period in the Shanghai market (sub-sample 1-1), returns of SSEC from 1995 to 2005 fail to reject the null hypothesis of the random walk under homoscedasticity and heteroscedasticity, except for Z(q) in lag 2, which rejects the null hypothesis. This suggests that the return series of the two markets has a random walk pattern from 1995 to 2005. The other 4 sub-sample periods do follow a random walk since the Z(q) and Z*(q) statistics fail to reject the null hypothesis. The results of the Chow-Denning test are consistent with those of the Lo-Mackinlay variance ratio test.

Overall, the return patterns of both SSEC and SZSE exhibit similar characteristics. Neither market adheres to the random walk hypothesis throughout the full period and the first market period. However, when considering the markets in separate sub-periods, they both display a random walk pattern. These findings are consistent with Chung's (2006) research, which also revealed that the full period of the market did not follow a random walk, while the separate sub-periods did follow a random walk. He concluded that China's stock market has become more efficient over time. Nevertheless, to verify this conclusion, it is necessary to utilize non-linear methods such as entropy and Hurst exponent methods.

Table 5a. Results of Variance Ratio Test on SSEC

The table shows results of the variance ratio tests for returns on Shanghai Composite Index for the full period and other 6 sub-sample periods. The table report the variance ratio, VR(q) and the variance-ratio test statistics, Z(q) for homoscedastic increments and Z*(q) for heteroskedastic increments in parentheses for q = 2,4,8,16, which is the same q are used in Lo & Mackinlay (1988). The null hypothesis is that the variance ratios equal one and indicate the stock index return follow a random walk. Chow and Denning (1993) test results are also presented in the table. Lo-Mackinlay test assume to follow a normal distribution. The critical value is 1.65, 1.96 and 2.58 for 10%, 5% and 1% significant level. The critical values for Chow and Denning are 2.23, 2.49,3.02 for 10%, 5% and 1% significant level.

Shanghai Composite Index (SSEC)								
		whole sample	sub-sample 1	sub-sample 1-1	**sub-sample 2**	sub-sample 3	**sub-sample 4**	sub-sample 5
		1990-12-20 to 2021-07-07	1990-12-20 to 2005-12-30	1995-01-24 to 2005-12-30	2006-01-04 to 2009-01-05	2009-01-06 to 2014-03-31	2014-04-01 to 2016-06-01	2016-06-02 to 2021-07-07
period		full period	regular	regular	bull and bust period	regular	bull and bust period	regular
lag2	VR(q)	1.047	1.056	1.036	0.996	1.014	1.075	1.003
	Z(q)	(4.02***)	(3.29***)	(1.76*)	(-0.12)	(0.51)	(1.73)	(0.09)
	Z*(q)	(1.83*)	(1.66*)	(0.74)	(-0.09)	(0.46)	(1.17)	(0.07)
lag4	VR(q)	1.122	1.157	1.035	1.0005	1.029	1.052	1.049
	Z(q)	(5.63***)	(4.93***)	(0.908)	(0.0009)	(0.57)	(0.64)	(0.92)
	Z*(q)	(2.33**)	(2.24**)	(0.38)	(0.007)	(0.49)	(0.43)	(0.73)
lag8	VR(q)	1.217	1.128	1.013	1.084	1.033	1.148	0.987
	Z(q)	(6.32***)	(5.33***)	(0.22)	(0.88)	(0.40)	(1.16)	(-0.15)
	Z*(q)	(2.54**)	(2.34**)	(0.096)	0.73	(0.35)	(0.77)	(-0.12)
lag16	VR(q)	1.268	1.311	0.923	1.19	1.08	1.229	0.927
	Z(q)	(5.25***)	(4.15***)	(-0.86)	1.35	(0.65)	(1.2)	(-0.58)
	Z*(q)	(2.27**)	(1.97**)	(-0.43)	1.13	(0.55)	(0.84)	(-0.46)
chow-Denning	Z(q)	(6.32***)	(5.33***)	(1.76)	(1.36)	(0.65)	(1.73)	(0.92)
	Z*(q)	(2.54**)	(2.35*)	(0.74)	(1.12)	(0.55)	(1.17)	(0.73)

*** p<0.01, ** p<0.05, * p<0.1

Table 5b. Results of Variance Ratio Test on SSEC

The table shows the results of the variance ratio tests for returns on Shenzhen Component Index for the full period and other 6 sub-sample periods. The table 5b present same information as table 5a.

Shenzhen Component Index (SSEC)						
	whole sample	sub-sample 1	**sub-sample 2**	sub-sample 3	**sub-sample 4**	sub-sample 5
	1995-01-24 to 2021-07-07	1995-01-24 to 2005-12-30	2006-01-04 to 2009-01-05	2009-01-06 to 2014-03-31	2014-04-01 to 2016-06-01	2016-06-02 to 2021-07-07

period		full period	regular	bull and bust period	regular	bull and bust period	regular
lag2	VR(q)	1.043	1.04	1.04	1.03	1.09	1.004
	Z(q)	(3.50***)	(2.17**)	(1.11)	(1.31)	(2.05**)	(0.165)
	Z*(q)	(2.25**)	(1.2)	(0.95)	(1.25)	(1.47)	(0.139)
lag4	VR(q)	1.071	1.09	1.03	1.05	1.12	1.018
	Z(q)	(3.05***)	(2.51**)	(0.46)	(0.86)	(1.53)	(0.33)
	Z*(q)	(1.92*)	(1.35)	(0.41)	(0.78)	(1.07)	(0.28)
lag8	VR(q)	1.129	1.15	1.14	1.02	1.26	0.98
	Z(q)	(3.51***)	(2.67***)	(1.28)	(0.29)	(2.01**)	(-0.26)
	Z*(q)	(2.19**)	(1.42)	(1.12)	(0.26)	(1.411)	(-0.22)
lag16	VR(q)	1.19	1.18	1.25	1.08	1.36	0.99
	Z(q)	(3.49***)	(2.15**)	(1.55)	(0.63)	(1.88*)	(-0.09)
	Z*(q)	(2.32**)	(1.26)	(1.37)	(0.56)	(1.37)	(-0.08)
chow-Denning	Z(q)	(3.51***)	(2.67**)	(1.55)	(1.31)	(2.05)	(0.32)
	Z*(q)	(2.32*)	(1.42)	(1.37)	(1.25)	(1.47)	(0.28)

*** p<0.01, ** p<0.05, * p<0.1

5.6 Entropy Tests

Tables 6a and 6b display the results of entropy tests on SSEC and SZSE for both price and return. According to previous research, sample entropy is more robust and less sensitive to changes in data length and exhibits greater consistency compared to approximate entropy (Yentes et al. 2012, Montesinos et al. 2018). Based on this, I have decided to use sample entropy as the primary measure for assessing market efficiency.

For both markets, the difference in entropy values on returns between periods is less pronounced than for prices, making it difficult to compare the efficiency levels across different periods using these results. Although the returns results do not provide a significant indicator of the Chinese stock market's efficiency level, we can observe an increase in entropy values on returns over time for both markets, with the highest values occurring in sub-sample 3 (2009-2014) - the period following the first boom-and-bust period. As a result, the subsequent analysis will focus on the entropy values obtained from the price data.

Comparing the entropy values across the entire period for both markets, I observe similar sample entropy values between the two. The SSEC has a sample entropy value of 0.0418, while the SZSE has a value of 0.0489. These results are consistent with traditional methods, indicating that the Chinese stock market as a whole was inefficient. Furthermore, the two markets as a whole have similar market efficiency level. In addition, the values of the individual sub-sample periods in both markets are higher than those for the full period, and the values increase over time. This suggests that both markets are becoming increasingly complex and further deviating less from efficiency.

Table 6a shows the entropy results of the SSEC. As shown, sample entropy values for price increase across sub-samples 1 to 5. Especially, there is a significant increase in entropy values after sub-sample 2. The values for sub-sample 3, 4, and 5 are 0.2467, 0.1724, and 0.299, respectively, but the values for the sub-sample 1 and 2 are 0.0602 and 0.0609. This indicates the first period of the Shanghai market is less efficient than other regular periods and the market is deviated less from efficiency after the 2008 Global Financial Crisis (after 2009). When comparing the results of the two bull-and-bust periods, both the entropy values during crises periods decreased from previous period. However, as the market environment developed, the second boom-and-bust period's entropy value (0.1724) was much higher than that of the first boom-and-bust period (0.0609).

I observe a similar trend in the Shenzhen market results, with the sample entropy values for prices increasing significantly over time. Table 6b shows that the entropy values for sub-sample 1 and sub-sample 2 are much lower than the values for other periods. Specifically, the entropy value for sub-sample 1 is 0.0779 and 0.0802 for sub-sample 2. In contrast, the entropy values for sub-sample 3, 4, and 5 are 0.2517, 0.1825, and 0.1701, respectively. Both bull-and-bust periods have lower entropy values compared to their previous period. It is noteworthy that the entropy value for sub-sample 5 of the Shenzhen stock market (0.17) is lower than that of the Shanghai stock market (0.299), suggesting that the Shenzhen market's ability to recover from the 2015 stock market crisis was weaker than that of the Shanghai market. A more detailed analysis of this can be found in the following section on time-varying entropy models.

By applying entropy methods, I am able to assess the level of market efficiency for each period of both markets. I find an upward trend in the entropy values for the Chinese stock market, excluding the crisis periods. This suggests that the market is becoming less deviated from an efficient market. Meanwhile, markets typically become more deviated from efficiency during crisis periods. In the following analysis, I will separate the bull and bust periods to compare the degree of efficiency between them.

Table 6a. Results of Entropy Tests on SSEC

The table displays the test results of permutation entropy (PE), Approximate Entropy (ApEn), and Sample Entropy (SampEn) on SSEC's price series and returns. The periods include the whole period and the other 6 sub-sample periods. Higher entropy value refers to more chaos in the return series. The bull-and-bust period results are highlighted in red color.

	Shanghai Composite index (SSEC) Entropy Tests Result						
	whole sample	sub-sample1	sub-sample1-1	sub-sample2	sub-sample3	sub-sample4	sub-sample5
	12/20/1990 to 2021-07-07	1990-12-20 to 2005-12-30	1995-01-24 to 2005-12-30	2006-01-04 to 2009-01-05	2009-01-06 to 2014-03-31	2014-04-01 to 2016-03-31	2016-06-02 to 2021-07-07
Period	full period	regular	regular	bull and bust	regular	bull and bust	regular
	Price						
PE(m=3)	0.8721	0.8646	0.8982	0.8852	0.897	0.9069	0.9103
ApEn(2,0.3)	0.0344	0.0476	0.0677	0.0474	0.1584	0.1337	0.2285
SampEn(2,0.2)	0.0418	0.0602	0.0937	0.0609	0.2467	0.1724	0.299
	Return						
PE(m=3)	0.9832	0.9831	0.9767	0.9785	0.9731	0.9750	0.9784

ApEn(2,0.3)	1.3794	1.2487	1.4598	1.4120	1.5504	1.1870	1.5062
SampEn(2,0.2)	1.3635	1.2138	1.6658	1.7727	1.9726	1.6087	1.8439

Table 6b. Results of Entropy Tests on SZSE

The table displays the test results of permutation entropy (PE), Approximate Entropy (ApEn), and Sample Entropy (SampEn) on SZSE with the whole period and the other 6 sub-sample periods. Higher entropy value refers to more chaos in the return series. The bull-and-bust period results are highlighted in red color.

	Shenzhen Component Index (SZSE) Entropy Tests Result					
	whole sample	sub-sample1	sub-sample2	sub-sample3	sub-sample4	sub-sample5
	1995-01-24 to 2021-07-07	1995-01-24 to 2005-12-30	2006-01-04 to 2009-01-05	2009-01-06 to 2014-03-31	2014-04-01 to 2016-03-31	2016-06-02 to 2021-07-07
Period	full period	regular	bull and bust	regular	bull and bust	regular
			Price			
PE(m=3)	0.8882	0.8972	0.8825	0.8986	0.9132	0.9115
AnEn(2,0.3)	0.034	0.0578	0.0509	0.158	0.1585	0.1219
SampEn(2,0.2)	0.0489	0.0779	0.0802	0.2517	0.1825	0.1701
			Return			
PE(m=3)	0.9830	0.9801	0.9809	0.9789	0.9770	0.9755
AnEn(2,0.3)	1.5028	1.4938	1.4328	1.5571	1.2968	1.5107
SampEn(2,0.2)	1.7092	1.6954	1.9099	2.0214	1.8295	1.8532

To better understand the efficiency patterns during crises, I divided sub-sample 2 (the first bull-and-bust period) and sub-sample 4 (the second bull-and-bust period) into the individual bull or bust period to conduct the entropy tests for each separated period. Tables 6c and 6d present the results of these tests. The first bull period, which ran from 2005-01-05 to 2007-10-16, occurred prior to the Global Financial Crisis, while the first bust period spanned from 2007-10-17 to 2009-01-05. The second bull period, which took place from 2014-04-01 to 2015-06-12, was before the Chinese 2015 stock market turbulence, and the second bust period lasted from 2015-06-13 to 2016-06-01.

For the Shanghai market, the values of the entropy test results during the bull period were significantly lower than those during the bust periods for both crises. For example, In the Shanghai stock market, during the first bull period, the sample entropy value on price is 0.021, while during the first bust period, it is 0.0933. Similarly, during the second bull period, the sample value is 0.0652, while during the second bust period, it is 0.3672. This finding indicates that the bull market deviates more from efficiency than the bear market even though the price pattern is momentously going in the same direction during these two periods. The Shenzhen market exhibited similar results, with entropy values during the bull periods lower than those during the bust periods. This suggests that series during the bull periods were less chaotic and easier to predict than those during the bust periods.

The reason why the bull market is less efficient can be attributed to the effect of the overconfidence bias on investor behaviors and on stock market reactions. According to Daniel et al. (1998), overconfident investors tend to overreact to private signals. During bull markets, individual investors may attribute too much of their success to their own abilities, leading to overconfidence, as posited by Gervais and Odean (2001). Additionally, investors may become overly optimistic and confident about the future price of the market, ignoring or downplaying potential risks or warnings during sustained periods of price increase. Ho et al. (2022) found evidence of overreaction in the Chinese stock market based on information disclosure rating. They suggest that investors rely too much on official sources and follow the herd when exposed to large amounts of information, leading to a more serious continuing overreaction in the market. Wu (2011) also supports the overreaction hypothesis in the Chinese stock market.

To summarize, our findings suggest that entropy values in both markets have increased over time. During the bull market period, entropy values were lower compared to the bust period, indicating that the degree of efficiency of bull market was low. This may be due to investors' tendency to overreact to market information during the bull market. Furthermore, both markets showed a significant entropy increase after sub-sample 2 (the first bull-and-bust period). It is worth noting that the implementation of the split-share reform by the Chinese government on April 29, 2005, aimed at converting non-tradable shares into tradable shares, could have been a significant event that contributed to increasing efficiency in the Chinese stock market's price level.

Table 6c. Results of Entropy Tests on SSEC based on Separated Bull and Bust Period

The table displays the test results of permutation entropy (PE), Approximate Entropy (ApEn), and Sample Entropy (SampEn) on SSEC with the two bull-and-bust periods. Higher entropy value refers to more chaos in the return series. The bull periods are highlighted in red color.

Shanghai Composite index(SSEC) Entropy Tests Result on Separated Bull and Bust Period

	sub-sample 2	sub-sample 2 bull	sub-sample2 bust	**sub-sample 4**	sub-sample 4 bull	sub-sample4 bust
	2006-01-04 to 2009-01-05	2005-01-04 to 2007-10-16	2007-10-17 to 2009-01-05	2014-04-01 to 2016-06-01	2014-04-01 to 2015-06-12	2015-06-13 to 2016-06-01
Period	bull and bust period	first bull period	first bust period	bull and bust period	second bull period	second bust period
			Price			
PE(m=3)	0.8721	0.8775	0.9049	0.9069	0.8781	0.9385
ApEn(2,0.3)	0.0344	0.0336	0.0933	0.1337	0.0732	0.3484
SampEn(2,0.2)	0.0418	0.0201	0.1168	0.1724	0.0652	0.3672
			Return			
PE(m=3)	0.9832	0.9775	0.9763	0.9750	0.9698	0.9697
ApEn(2,0.3)	1.3794	1.4029	1.3000	1.1870	1.1423	1.0209
SampEn(2,0.2)	1.3635	1.9101	2.0740	1.6087	1.7814	1.6229

Table 6d. Results of Entropy Tests on SZSE based on Separated Bull and Bust Period

The table displays the test results of permutation entropy (PE), Approximate Entropy (ApEn), and Sample Entropy (SampEn) on SZSE with the two bull-and-bust periods. Higher entropy value refers to more chaos in the return series. The bull periods are highlighted in red color.

Shenzhen Component Index (SZSE) Entropy Tests Result on Separated Bull and Bust Period

	sub-sample 2	sub-sample 2 bull	sub-sample2 bust	**sub-sample 4**	sub-sample 4 bull	sub-sample4 bust
	2006-01-04 to 2009-01-05	2006-01-04 to 2007-10-31	2007-11-01 to 2009--01-05	2014-04-01 to 2016-06-01	2014-04-01 to 2015-06-12	2015-06-13 to 2016-06-01
Period	bull and bust period	first bull period	first bust period	bull and bust period	second bull period	second bust period
			Price			
PE(m=3)	0.8825	0.8751	0.8987	0.9132	0.9053	0.9449

ApEn(2,0.3)	0.0509	0.0416	0.1082	0.1585	0.0762	0.3998
SampEn(2,0.2)	0.0802	0.0336	0.1609	0.1825	0.0666	0.4924
Return						
PE(m=3)	0.9809	0.9762	0.9690	0.9770	0.9743	0.9678
ApEn(2,0.3)	1.4328	1.3207	1.2225	1.2968	1.3171	1.0681
SampEn(2,0.2)	1.9099	1.8973	2.0943	1.8295	2.0516	1.8931

5.7 Hurst Exponent Test

The Hurst Exponent values for SSEC and SZSE's log price and returns are shown in Tables 7a and 7b. For both markets' prices, the Hurst exponent is approximately 0.8, which means the price is highly correlated to yesterday's price and has a positive correlation. Hurst exponent for the return series in the Shanghai stock market is around 0.5, particularly in sub-sample 1-1 from 1995 to 2005 and the last sub-sample period from 2016 to 2021, where the Hurst Exponent values are 0.5115 and 0.5129, respectively. These values suggest that there is no predictable pattern in the daily change in price during these periods, and the series follows a random walk. Sub-sample 2, which covers the 2008 Financial Global Crisis, has a high Hurst Exponent value (0.6308), indicating a momentum effect during the crisis. A similar pattern can be observed in the second bull-and-bust period, where the Hurst Exponent is 0.5847. Excluding these two bull-and-bust periods, the return series is closer to a random walk over time. Similar results are observed in SZSE's data, with sub-sample 2 and sub-sample 4 having higher Hurst Exponent values (0.6266 and 0.5677), and sub-sample 3 and sub-sample 4 having Hurst Exponent values close to 0.5. Overall, the Hurst Exponent of the Shenzhen market is higher than that of the Shanghai stock market.

Table 7c and 7d display the results of the Hurst Exponent analysis for the bull and bust periods separately. During the bull period, the Hurst Exponent values on the return series are greater than 0.5, while during the bust period, the values are closer to 0.5. For instance, the Hurst

Exponent values for the first bull market (2005-2007) and the second bull market (2014-2015) were 0.57 and 0.56, respectively, compared to 0.48 and 0.52 for their respective bust periods in the Shanghai market. These results are consistent with the entropy analysis, which shows that the bull market is less efficient than the bust period in the Chinese stock market. However, these findings are only significant in the return series.

The time series Hurst exponent analysis, as shown in Figure 18 and 19 in the Appendix, reveals that the portion of Hurst exponent values larger than 0.5 and smaller than 0.5 are equally distributed during the last period (2016-2021) for both markets. Prior to the last period, most of the Hurst exponent values were larger than 0.5 for both markets. The graph patterns suggest that price changes in both markets are becoming more efficient and less predictable, as it is increasingly difficult to discern any patterns in the series.

Table 7a Hurst Exponent Results on SSEC

The table shows SSEC's Hurst exponent results on log price and returns for full period and each 6 sub-sample periods. Hurst exponent equals 0.5, referring to the series following a random walk. If the value is larger than 0.5, the series is momentum; otherwise, the series is mean reverting. The bull-and-bust period results are highlighted in red color.

	Shanghai Composite index (SSEC) Hurst Exponent Results						
	whole sample	sub-sample1	sub-sample1-1	sub-sample2	sub-sample3	sub-sample4	sub-sample5
	12/20/1990 to 2021-07-07	1990-12-20 to 2005-12-30	1995-01-24 to 2005-12-30	2006-01-04 to 2009-01-05	2009-01-06 to 2014-03-31	2014-04-01 to 2016-03-31	2016-06-02 to 2021-07-07
Period	full period	regular	regular	bull and bust	regular	bull and bust	regular
Log Price							
Hurst Exponent	0.8867	0.8754	0.8763	0.8816	0.883	0.8564	0.8637
Return							
Hurst Exponent	0.5328	0.5472	0.5115	0.6308	0.5366	0.5847	0.5129

Table 7b Hurst Exponent Results on SZSE

The table shows SZSE's Hurst exponent results on log price and returns for full period and each 6 sub-sample periods. Hurst exponent equals 0.5, referring to the series following a random walk. If the value is larger than 0.5, the series is momentum; otherwise, the series is mean reverting. The bull-and-bust period results are highlighted in red color.

	Shenzhen Component Index (SZSE) Hurst Exponent Results					
	whole sample	sub-sample1	sub-sample2	sub-sample3	sub-sample4	sub-sample5
	1995-01-24 to 2021-07-07	1995-01-24 to 2005-12-30	2006-01-04 to 2009-01-05	2009-01-06 to 2014-03-31	2014-04-01 to 2016-03-31	2016-06-02 to 2021-07-07
Period	full period	regular	bull and bust	regular	bull and bust	regular
Log Price						
Hurst Exponent	0.9056	0.8584	0.8736	0.8796	0.8548	0.8425
Return						
Hurst Exponent	0.5379	0.5747	0.6266	0.5346	0.5677	0.5410

Table 7c Hurst Exponent Results on SSEC based on Separated Bull and Bust Period

The table shows SSEC's Hurst exponent results on log price and returns for full period and each 6 sub-sample periods on the separated bull and bust period. Hurst exponent equals 0.5, referring to the series following a random walk. If the value is larger than 0.5, the series is momentum; otherwise, the series is mean reverting. The bull period results are highlighted in red color.

Shanghai Composite index(SSEC) Hurst Exponent Results on Separated Bull and Bust Period						
	sub-sample 2	sub-sample 2 bull	sub-sample2 bust	**sub-sample 4**	sub-sample 4 bull	sub-sample4 bust
	2006-01-04 to 2009-01-05	2005-01-04 to 2007-10-16	2007-10-17 to 2009-01-05	2014-04-01 to 2016-06-01	2014-04-01 to 2015-06-12	2015-06-13 to 2016-06-01
Period	bull and bust period	first bull period	first bust period	bull and bust period	second bull period	second bust period
Log Price						
Hurst Exponent	0.8816	0.869	0.855	0.8564	0.857	0.822
Return						
Hurst Exponent	0.6308	0.5730	0.4766	0.5847	0.5573	0.5240

Table 7d Hurst Exponent Results on SSEC based on Separated Bull and Bust Period

The table shows SSEC's Hurst exponent results on log price and returns for full period and each 6 sub-sample periods on the separated bull and bust period. Hurst exponent equals 0.5, referring to the series following a random walk. If the value is larger than 0.5, the series is momentum; otherwise, the series is mean reverting. The bull period results are highlighted in red color.

Shenzhen Component Index (SZSE) Hurst Exponent Results on Separated Bull and Bust Period						
	sub-sample 2	sub-sample 2 bull	sub-sample2 bust	**sub-sample 4**	sub-sample 4 bull	sub-sample4 bust
	2006-01-04 to 2009-01-05	2006-01-04 to 2007-10-31	2007-11-01 to 2009--01-05	2014-04-01 to 2016-06-01	2014-04-01 to 2015-06-12	2015-06-13 to 2016-06-01
Period	bull and bust period	first bull period	first bust period	bull and bust period	second bull period	second bust period
Log Price						
Hurst Exponent	0.8736	0.868	0.858	0.8548	0.859	0.8015
Return						
Hurst Exponent	0.6266	0.5343	0.4937	0.5677	0.5714	0.5240

5.8 Time-varying degree of market efficiency -- Entropy Time Series Results

To gain further insight into the degree of market efficiency in Chinese stock indexes, I employ entropy models with a rolling window of 126 days. The degree of market efficiency tells us how the market differs from an efficient market. In section 4.2.5.4, a simulation model experiment was conducted, wherein a series is considered random if the sample entropy value is greater than 2 or the approximate entropy value is greater than 0.8. For permutation entropy, if the value exceeds 0.95, the series is deemed random. Therefore, if at time t, the sample entropy or approximate entropy value is greater than 2 or 0.8, respectively, or if the permutation entropy value exceeds 0.95, the market is considered efficient at that time.

Figures 14 and 15 display the entropy results for SSEC and SZSE, respectively. Consistent with our simulation experiments, the variance of permutation entropy is too small to analyze the degree of market efficiency for both markets. Moving on to approximate entropy and sample entropy (Figure 14.2), I first observe that the entropy value of ssec and szse's price changes over time for both markets, which means the degree of market efficiency changes over time. Meanwhile, I find that sample entropy has a higher variance and entropy value than approximate entropy, likely due to the latter's more stringent regularity in algorithms. Additionally, the entropy values have a shape decline to the lowest value around 0.1 for both markets, six months before the onset of the crisis, indicating that sample entropy and approximate entropy could be effective early warning signals for a crisis. However, the signal to estimate the market's recovery is less clear and may take longer to catch up with the market's trend.

For the Shanghai stock market, the range of sample entropy value is from 0.03 to 1.49, and the range of approximate entropy is from 0.026 to 0.89. Figure 14.3 shows the markets deviate more from market efficiency during the boom-and-bust period. The sample entropy value remained consistently low during the crisis periods, ranging from 0.17 to 0.9 for the first boom-and-bust period (2005 – 2009) and 0.14 to 1 for the second boom-and-bust period (2014 – 2016). The market efficiency was less deviated from efficiency during the periods after the boom-and-bust periods. The highest sample entropy values were observed in late 2014 and 2021(1.49 and 1.45, respectively). Sub-sample 5 (2016 to 2021) has an average higher entropy value than sub-sample 3(2009-2014), indicating the market efficiency evolved to be less deviated from efficiency. Similar results were observed for approximate entropy. Notably, the highest approximate entropy values in 2014 and 2021 were above the 0.8 market efficient threshold, further confirming that the degree of Shanghai market efficiency is improving after the crisis.

For the Shenzhen market, the sample entropy ranges from 0.1 to 1.54 and the approximate entropy ranges from 0.1 to 0.83. The highest sample entropy values happened in 1998 (1.4), 2011 (1.54), and 2021 (1.45), indicating the degree of efficiency increased after the crisis as well. Similar to the Shanghai market, entropy values dropped to the lowest value during the boom-and-bust period to 0.1. When comparing the entropy values of sub-sample 3 (2009 -2014) and sub-sample 5 (2016-2021), sub-sample 3 has slightly higher entropy values than sub-sample 5. This finding contrasts with the Shanghai market, suggesting that the Shenzhen market took longer to recover than the Shanghai market after the 2015 stock market crash. The slow recovery in the Shenzhen stock market could be due to the fact that it has a higher proportion of small and medium-sized companies listed, particularly in the technology and innovation sectors. These companies are generally more susceptible to volatility and risk than the larger state-owned enterprises that dominate the Shanghai market. Moreover, the majority of bubbles occur in technology companies because government policies encourage the development of technology companies, leading to a large influx of hot money into the technology sector. There is also a high proportion of securities firms' financing and off-exchange margin trading before the 2015 crisis happens, which contributed to the 2015 crisis. Therefore, these factors caused the Shenzhen stock market to require more time to recover than the Shanghai market.

In conclusion, the degree of market efficiency of the Shanghai stock market and the Shenzhen stock market has varied over time based on the market environment. Normally, the market efficiency deviates less from efficiency during regular periods compared with the boom-and-bust period. I also observe the degree of market efficiency increase after major policies or events happened, consistent with the adaptive market hypothesis, which suggests that market participants can be irrational in highly uncertain markets but will evolve dynamically to improve efficiency. Additionally, with the completion of the split-share reform, the approval of QFII, and the launch of margin trading and short selling, the markets have become more diverse and open with increased investment options for participants. While approximate entropy showed a similar pattern to sample entropy, the latter is suggested for analyzing the degree of market efficiency, as it has a larger variance. Furthermore, sample entropy may serve as a useful early warning signal for predicting stock market crises.

Figure 14. Entropy Tests Plots on SSEC Price with rolling window N = 126

The following graphs from figure 14.1 to 14.4 showed the relationship among Permutation Entropy, Sample Entropy, and Approximate Entropy with SSEC price. The blue line is the PE value, the green line is sample entropy(m =2, r =0.2*sd), and the red line is approximate entropy(m= 2, r = 0.3*sd). Orange blocks represent two bull and bust periods in the Shanghai stock market: the 2008 Global Financial Crisis(2005-01-04 to 2009-01-05) and the 2015 market turberlance (2014-04-01 to 2016-06-01). Purple lines show the major events: QFII(2003-07-09), Split-share reform(2005-04-29), CSI300(2010-04-16), and Shanghai-Hongkong link(2014-11-17)

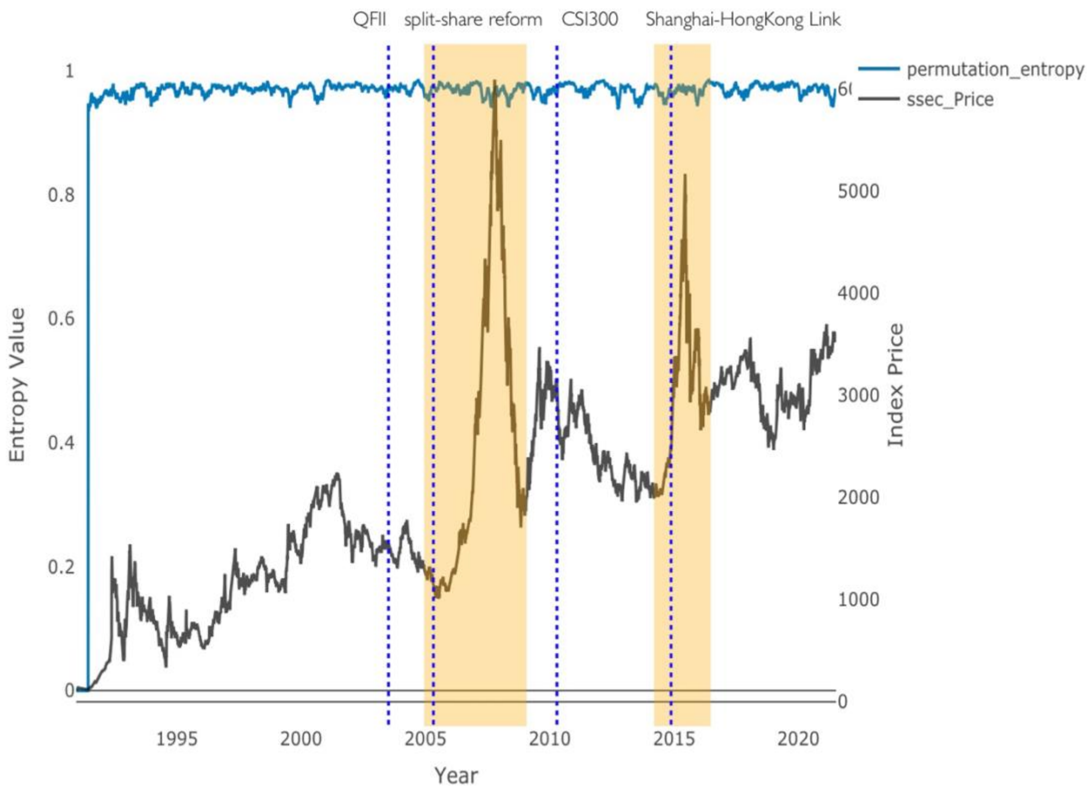


Figure 14.1 Permutation Entropy on SSEC price with 126 days rolling window

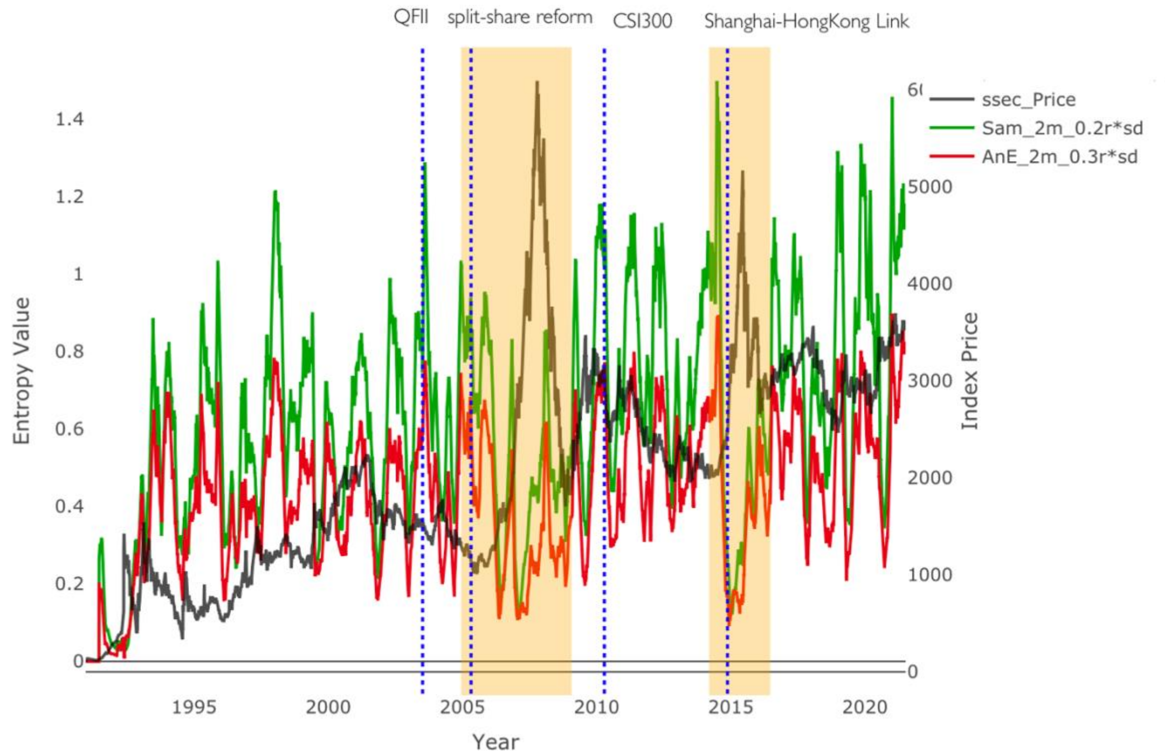


Figure 14.2 Sample Entropy and Approximate Entropy plots on SSEC price with 126 days rolling window

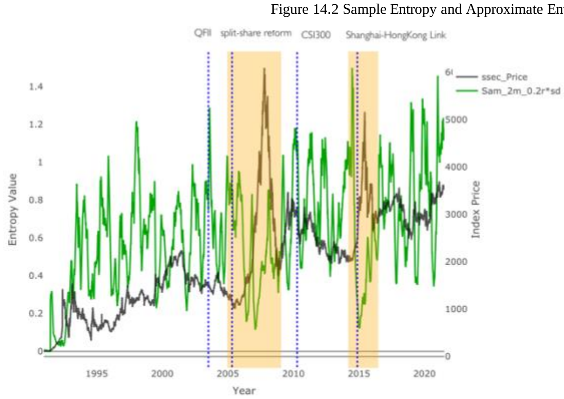


Figure 14.3 Sample Entropy on SSEC price with m =2, r = 0.2*sd with 126 days rolling window

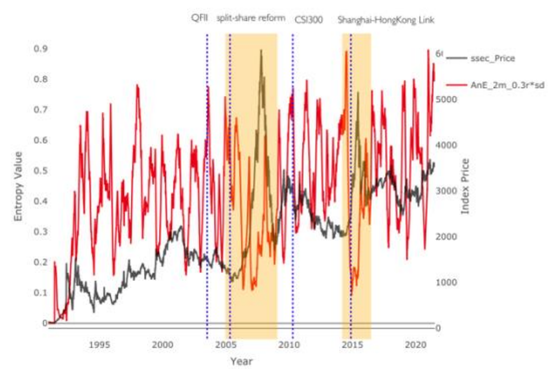


Figure 14.4 Approximate Entropy on SSEC price with m =2, r = 0.3*sd with 126 days rolling window

Figure 15. Entropy Tests Plots on SZSE Price with rolling window N = 126

The following graphs from figure 15.1 to 15.4 showed the relationship among Permutation Entropy, Sample Entropy, and Approximate Entropy with SZSE price. The blue line is the PE value, the green line is sample entropy(m =2, r =0.2*sd), and the red line is approximate entropy(m= 2, r = 0.3*sd). Orange blocks represent two bull and bust periods in the Shenzhen stock market: the 2008 Global Financial Crisis(2006-01-04 to 2009-01-05) and the 2015 market turbulence (2014-04-01 to 2016-06-01). Purple lines show the major events: QFII(2003-07-09), Split-share reform(2005-04-29), CSI300(2010-04-16), and Shenzhen-Hongkong link(2016-08-16)

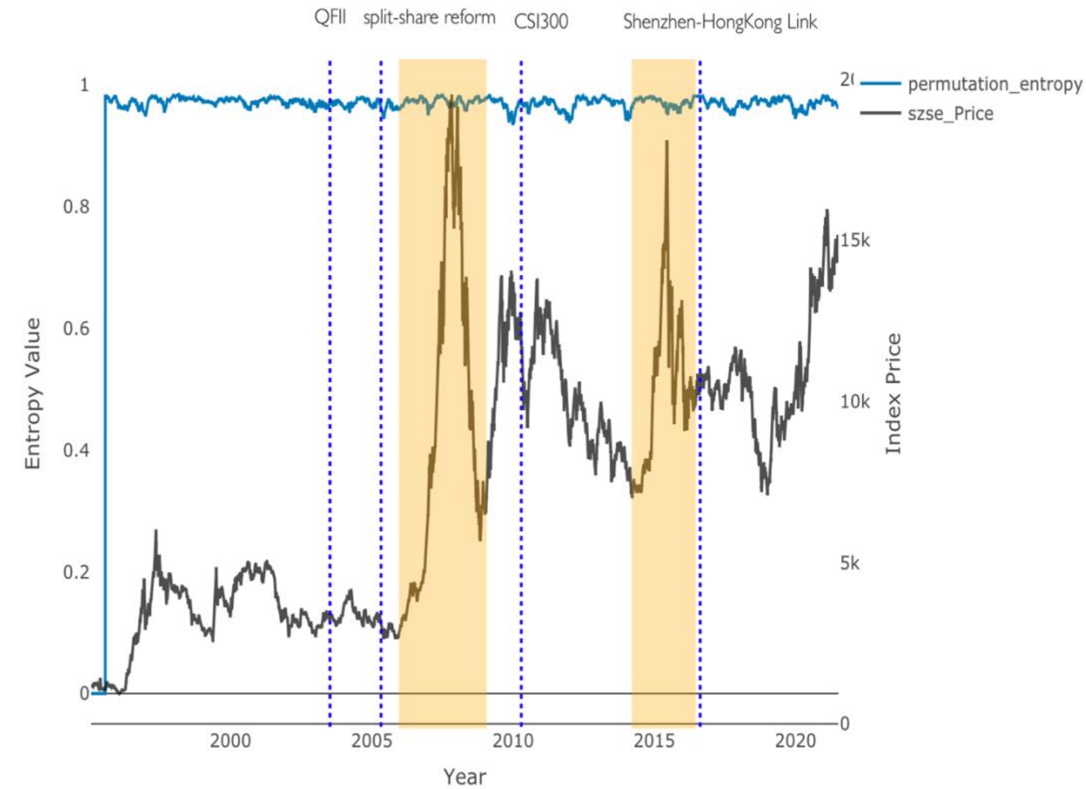


Figure 15.1 Permutation Entropy on SZSE price with 126 days rolling window

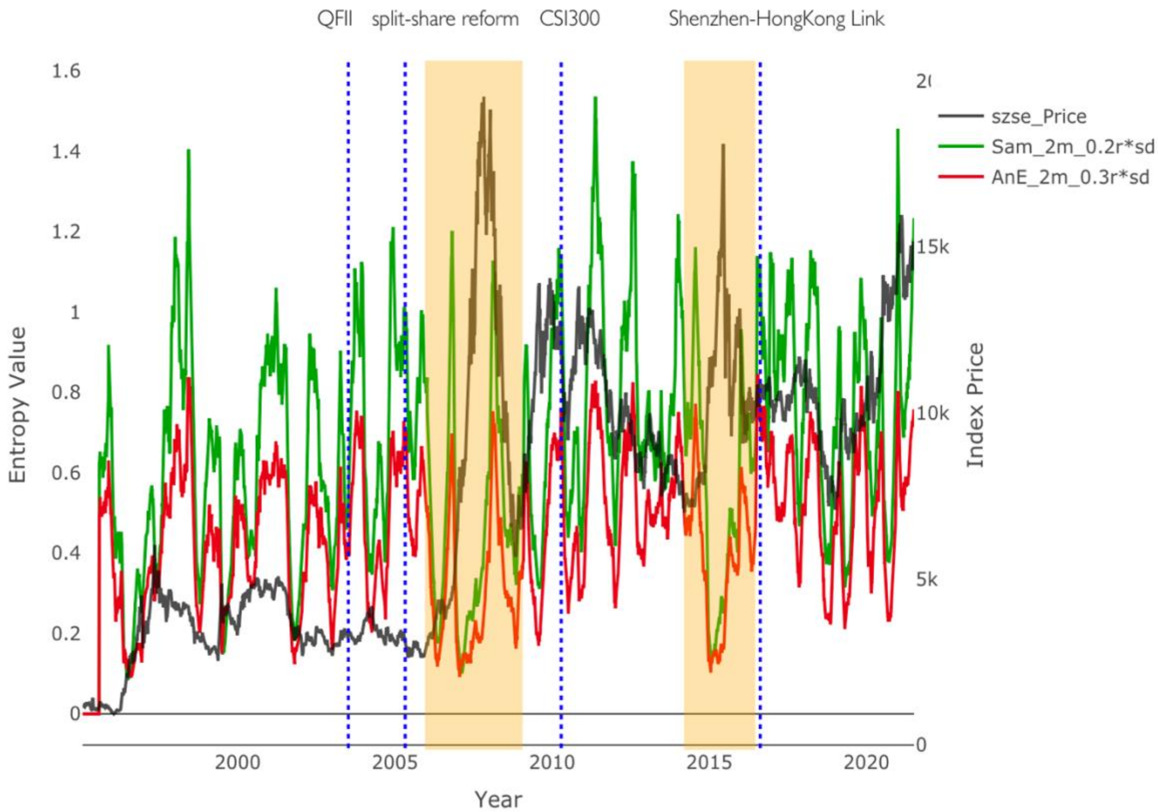


Figure 15.2 Sample Entropy and Approximate Entropy plots on SZSE price with 126 days rolling window

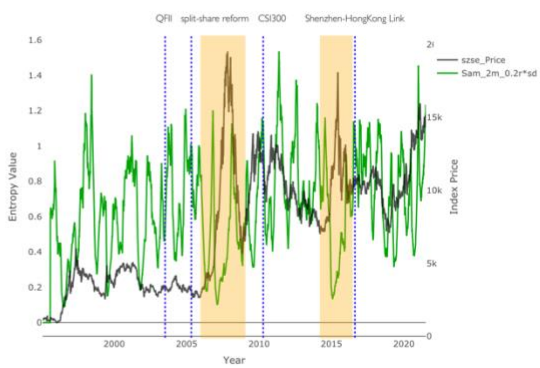


Figure 15.3 Sample Entropy on SZSE price with m =2, r = 0.2*sd with 126 days rolling window

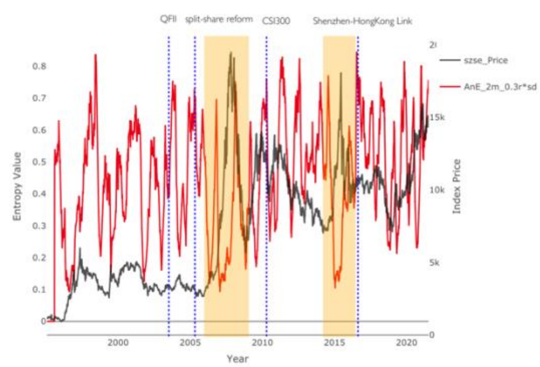


Figure 15.4 Approximate Entropy on SZSE price with m =2, r = 0.3*sd with 126 days rolling window

5.9 Major Findings of the Study

To test the weak-form efficiency hypothesis, it is necessary to determine whether successive price changes or returns are correlated with their past values. In this study, I first employed traditional methods, including serial correlation tests, runs tests, ADF tests, and variance ratio tests, to examine weak-form efficiency in the Chinese stock market. Results from the four methods were generally consistent, except for the ADF test, which produced somewhat mixed results. While the ADF test found no random walk (efficiency) in all sample periods for both markets,, the other three tests showed that price changes followed a random walk after the first sub-sample period. It's important to note that unit root tests are not ideal for testing market efficiency since they only consider the mean of returns and ignore the volatility of returns. As we discussed earlier, this is a limitation of using unit root tests to evaluate market efficiency.

To make the two markets comparable, I added another sub-sample from 1995 to 2005 in the Shanghai market. The interesting finding is that price changes in the first 5 years of the Shanghai market did not follow a random walk, but the period from 1995 to 2005 did exhibit weak-form efficiency. In contrast, the first period in the Shenzhen market, from 1995 to 2005, did not show a random walk behavior except for the runs test. However, runs test showed that all periods of the Shenzhen market exhibited weak-form efficiency.

Chinese stock market experienced two significant bull and bust periods. The first one was from 2006 to 2009, which included the 2008 Financial Global Crisis. The bull period was from 2005 to 2007, while the bust period was from 2014 to 2015. The second period was from 2014 to 2016, also known as the 2015 Chinses stock market turbulence. The ADF test consistently showed that the return series in all periods were not random, which is contradictory to the other three tests' results. So we only considered the results of the serial correlation test, runs test, and variance ratio test. For the Shanghai stock market, the tests for the first bull-and-bust period indicated that it followed a random walk. When we tested the efficiency of the bull and bust periods separately, the results showed that the bull period still followed a random walk, except for lag times greater than 30 days in the serial correlation test. The bust period followed a random walk based on all three tests. For the second bull-and-bust period, the serial correlation test indicated that it was not random, except for lag 2, while the runs test and variance ratio test showed that it followed a random walk. The tests indicated that the second bull period followed a random walk, but the results were contradictory when testing the bust period. The variance ratio test indicated that this period followed a random walk, and the serial correlation test also supported this, except for lag times of 10 and 30. However, the runs test rejected this conclusion. Similar contradictory results were found in the tests for the Shenzhen market.

Based on the above test results, we can conclude that if we combine the bull-and-bust periods, the three test results have a comparable result that the two markets are not random in full time range, but each period became more random over time, except for the bull-and-bust period. However, when we want to understand the efficiency on bull or bust period, the traditional tests may not provide a clear answer since the results are contradictory. The results for all periods are summarized in tables 10a and 10b, and table 10c and 10d were displayed the separated bull and bust period results.

Table 10a. Summarize the Traditional Test Results for SSEC

The table summarized the traditional methods' results on the return of SSEC. Not random means the test result indicates the return series do not follow a random walk, random means it follows random walk. The bull-and-bust period results are highlighted in red color.

	Shanghai Composite index (SSEC) Results on Return						
	whole sample	sub-sample1	sub-sample1-1	sub-sample2	sub-sample3	sub-sample4	sub-sample5
	12/20/1990 to 2021-07-07	1990-12-20 to	1995-01-24 to	2006-01-04 to	2009-01-06 to	2014-04-01 to	2016-06-02 to

		2005-12-30	2005-12-30	2009-01-05	2014-03-31	2016-03-31	2021-07-07
Period	full period	regular	regular	bull and bust	regular	bull and bust	regular
serial correlation test	**not random**	not random	random after lag 2	random	random	not random	random in lag1,2
ADF test (returns)	**not random**	not random	not random	not random	not random	not random	not random
runs test	**not random**	not random	random	random	random	random	random
variance ratio test	**not random**	not random	random	random	random	random	random

Table 10b. Summarize the Traditional Test Results for SZSE

The table summarized the traditional methods' results on the return of SZSE. Not random means the test result indicates the return series does not follow a random walk, random means it follows a random walk. The bull-and-bust period results are highlighted in red color.

	Shenzhen Component Index (SZSE) on Return					
	whole sample	sub-sample1	sub-sample2	sub-sample3	sub-sample4	sub-sample5
	1995-01-24 to 2021-07-07	1995-01-24 to 2005-12-30	2006-01-04 to 2009-01-05	2009-01-06 to 2014-03-31	2014-04-01 to 2016-03-31	2016-06-02 to 2021-07-07
Period	full period	regular	bull and bust	regular	bull and bust	regular
serial correlation test	not random	random after lag5	random in lag1,2	random after lag1	not random	random
ADF test (returns)	not random	not random	not random	not random	not random	not random
runs test	random	random	random	random	random	random
variance ratio test	not random	not random	random	random	random	random

Table 10c. Summarize the Traditional Test Results for SSEC on Separated Bull and Bust Period

The table summarized the traditional methods' results on the return of SSEC on separated bull and bust period. Not random means the test result indicates the return series does not follow a random walk, random means it follows a random walk. The bull period results are highlighted in red color.

Shanghai Composite index (SSEC) Results on Return of Separated Bull and Bust Period						
	sub-sample 2	sub-sample 2 bull	sub-sample2 bust	**sub-sample 4**	sub-sample 4 bull	sub-sample 4 bust
	2006-01-04 to 2009-01-05	2005-01-04 to 2007-10-16	2007-10-17 to 2009-01-05	2014-04-01 to 2016-03-31	2014-04-01 to 2015-06-12	2015-06-13 to 2016-06-01

Period	bull and bust	first bull period	first bust period	bull and bust	second bull period	second bust period
serial correlation test	random (except lag5,10)	random (except lag30)	random	not random (except lag 2)	random (except lag5)	random (except lag10,30)
ADF test(returns)	not random	not random	not random	not random	not random	not random
runs test	random	random	random	random	random	not random
variance ratio test	random	random	random	random	random	random

Table 10d. Summarize the Traditional Test Results for SZSE on Separated Bull and Bust Period

The table summarized the traditional methods' results on the return of SZSE on separated bull and bust period. Not random means the test result indicates the return series does not follow a random walk, random means it follows a random walk. The bull period results are highlighted in red color.

Shenzhen Component Index (SZSE) Results on Return of Separated Bull and Bust Period						
	sub-sample 2	sub-sample 2 bull	sub-sample 2 bust	**sub-sample 4**	sub-sample 4 bull	sub-sample4 bust
	2006-01-04 to 2009-01-05	2006-01-04 to 2007-10-31	2007-11-01 to 2009--01-05	2014-04-01 to 2016-06-01	2014-04-01 to 2015-06-12	2015-06-13 to 2016-06-01
Period	bull and bust	first bull period	first bust period	bull and bust period	second bull period	second bust period
serial correlation test	random (except lag 5, 10,30)	random	random	not random (except lag2)	random	random (except lag 10,30)
ADF test(returns)	not random	not random	not random	not random	not random	not random
runs test	random	random	not random	random	random	random
variance ratio test	random	random	random	random	random	random

To assess the level of uncertainty across the five sub-sample periods and understand the degree of efficiency on the bull and bust period separately, complexity methods were employed in this study. The entropy values for both Chinese stock markets increased significantly after sub-sample 2 (after 2009), indicating an increase in market efficiency over time. Moreover, full period entropy values were observed to be lower compared to those of each sub-sample period, indicating higher efficiency levels in the shorter sub-periods. The market experienced a decrease in efficiency levels after the 2015 stock market turbulence in China, and may have been further impacted by the

COVID-19 pandemic in 2020. Additionally, it was also observed that entropy values were lower during bull periods compared to bust periods, suggesting that investors in the Chinese market may be more prone to overreacting to information during bullish market conditions.

According to the Hurst exponent analysis, the Chinese market has become more efficient over time, which is consistent with other tests. However, during bull-and-bust periods, the market tends to be inefficient. Specifically, the Hurst exponents during these periods were around 0.6, suggesting that price changes tended to move in the same direction. As time progressed, the Hurst exponents approached 0.5, indicating that the returns of the Chinese stock market gradually lost their long-term memory. Therefore, the Hurst exponent analysis provides further evidence that the Chinese stock market has become more efficient over time and that inefficiencies are more likely to occur during bull-and-bust periods. All in all, the complex analysis does not contradict the traditional results but complements traditional measures of efficiency by capturing the degree of randomness present in the data, which can enhance our understanding of market dynamics.

Chapter 6 Conclusion

The empirical results of this study suggest that the Chinese stock market efficiency varies over time, with the most efficient period from 2009 to 2014 and 2016 to 2021which are the periods after the boom-and-bust period. Both traditional and complexity methods suggest that the Chinese stock market as a whole is inefficient, but there are sub-sample periods that exhibit weak-form efficiency. Comparing both methods, traditional methods, constrained by their linearity assumption and the “all-or-none” conclusion, cannot quantify the degree of market efficiency as effectively as complexity methods can. Complexity methods reveal that the degree of the Chinese stock market efficiency varies over time but displays an increasing trend, indicating that the market is deviating less from efficiency as it develops, characterized by improved liquidity and a broader range of trading techniques. This also implies that market participants can learn from past mistakes and that all agents and instruments are dynamically evolving in this intricate environment. Additionally, this study contributes to the use of entropy values as a measure of the degree of efficiency of stock markets, as these methods could be utilized to detect phrase transition.

The future study could implement entropy methods on each sector's price or price change series. By quantifying the major sector's degree of randomness, the investors and government authorities could generate better strategy and policy to stabilize the market. Other complexity methods like recurrent plots or largest Lyapunov exponent can be also tested to quantify the randomness level. Moreover, bubble identification and prediction also can be considered in the future study. Lastly, it would be valuable to investigate the causes of inefficiency in the Chinese stock market to understand which behavioral biases and information limitations can explain periods when the market appears inefficient. This could provide insights into the varying performance of the market across different time periods.

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Appendix

Figure 17. Entropy Tests Plots on SSEC Return with rolling window N = 126

The following graphs from figure 17.1 to 17.4 showed the relationship among Permutation Entropy, Sample Entropy, and Approximate Entropy with SSEC return. The blue line is the PE value, the green line is sample entropy(m =2, r =0.2*sd), and the red line is approximate entropy(m= 2, r = 0.3*sd). Orange blocks represent two bull and bust periods in China's stock market: the 2008 Global Financial Crisis(2005-01-04 to 2009-01-05) and the 2015 market turbulence (2014-04-01 to 2016-06-01). Purple lines show the major events: QFII(2003-07-09), Split-share reform(2005-04-29), CSI300(2010-04-16), and Shanghai-Hongkong link(2014-11-17)

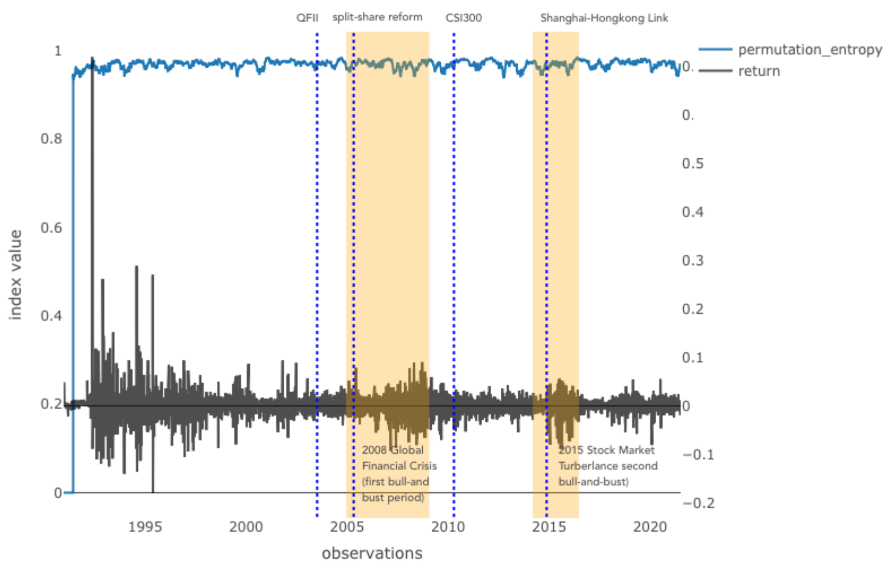

Figure 17.1 Permutation Entropy on SSE return with 126 days rolling window

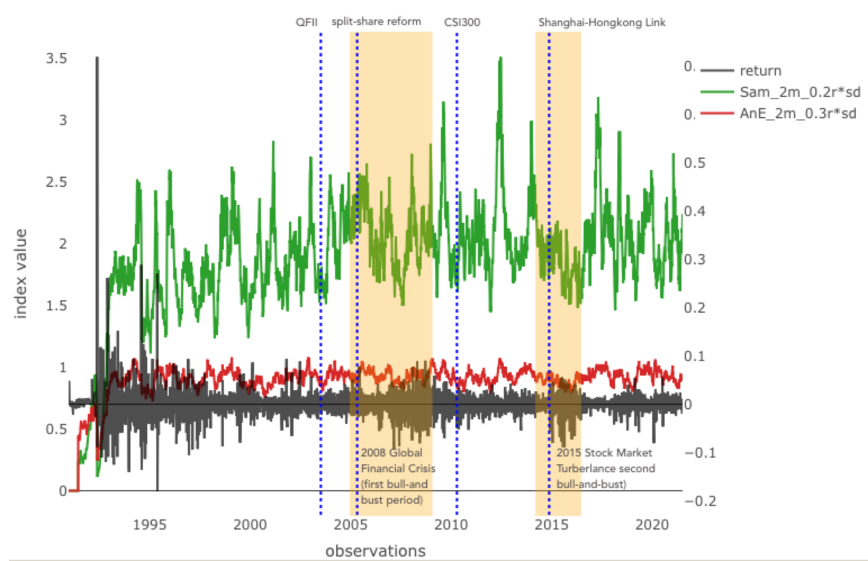

Figure 17.2 Sample Entropy and Approximate Entropy plots on SSEC return with 126 days rolling window

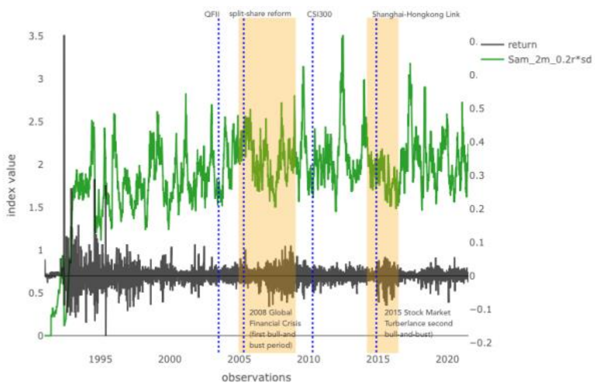

Figure 17.3 Sample Entropy on SSEC return with m =2, r = 0.2*sd with 126 days rolling window

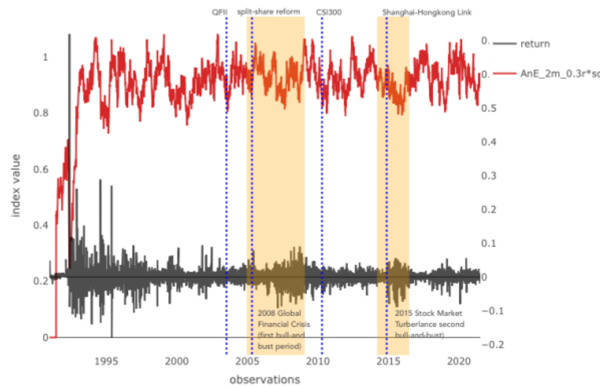

Figure 17.4 Approximate Entropy on SSEC return with m =2, r = 0.3*sd with 126 days rolling window

Figure 18. Entropy Tests Plots on SZSE Return with rolling window N = 126

The following graphs from figure 18.1 to 18.4 showed the relationship among Permutation Entropy, Sample Entropy, and Approximate Entropy with SZSE return. The blue line is the PE value, the green line is sample entropy(m =2, r =0.2*sd), and the red line is approximate entropy(m= 2, r = 0.3*sd). Orange blocks represent two bull and bust periods in China's stock market: the 2008 Global Financial Crisis(2005-01-04 to 2009-01-05) and the 2015 market turberlance (2014-04-01 to 2016-06-01). Purple lines show the major events: QFII(2003-07-09), Split-share reform(2005-04-29), CSI300(2010-04-16), and Shenzhen-Hongkong link(2016-08-16)

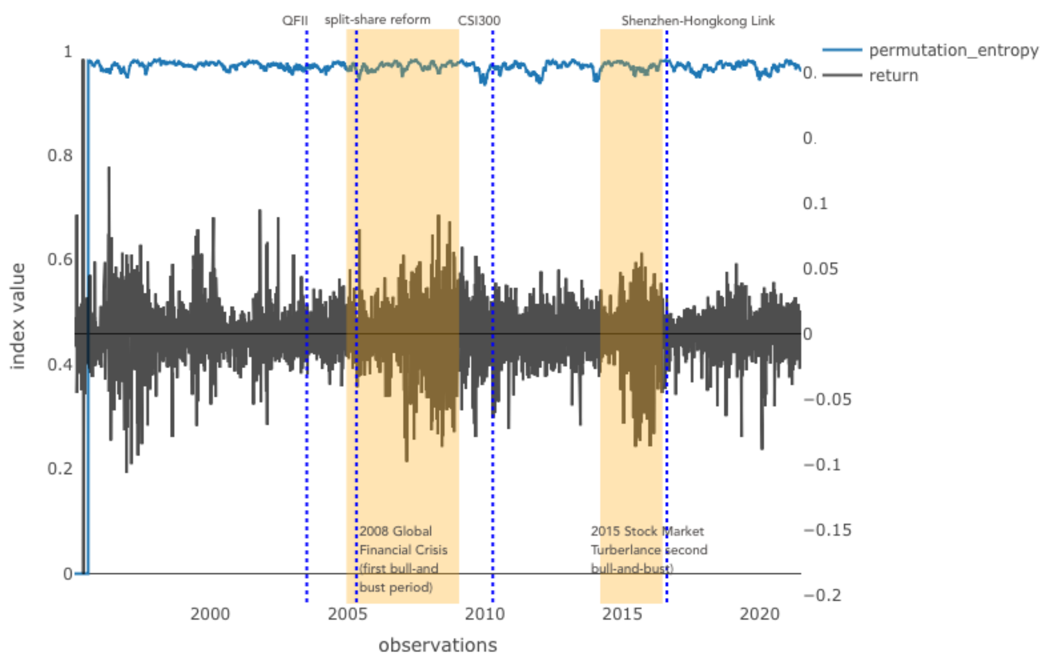

Figure 18.1 Permutation Entropy on SZSE return with 126 days rolling window

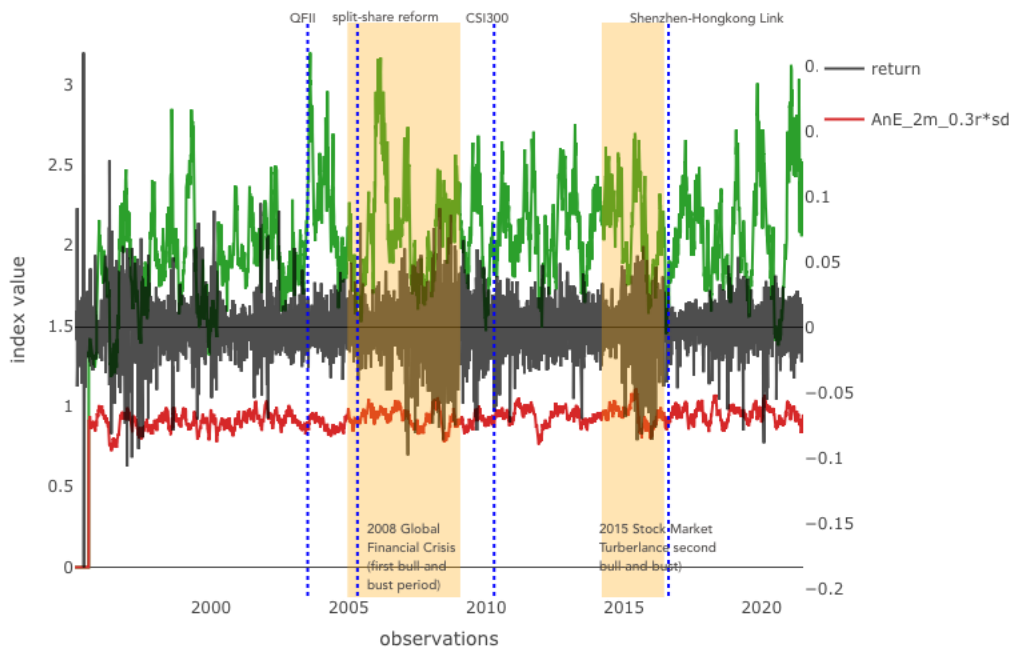

Figure 18.2 Sample Entropy and Approximate Entropy plots on SZSE return with 126 days rolling window

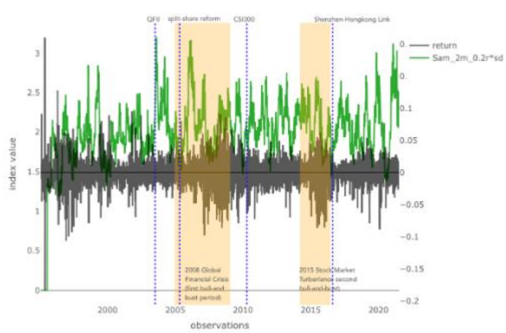

Figure 18.3 Sample Entropy on SZSE return with m =2, r = 0.2*sd with 126 days rolling window

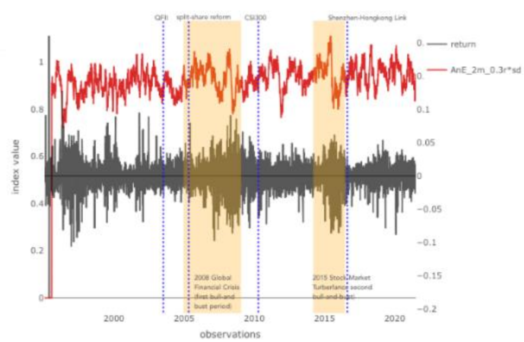

Figure 18.4 Approximate Entropy on SZSE return with m =2, r = 0.3*sd with 126 days rolling window

Figure 19. Hurst Exponent Tests Plots on SSEC and SZSE Price with rolling window N = 120

The following graphs from Figures 19.1 and 19.2 represent the Hurst Exponent time series plots on the price of SSEC and SZSE with 126 days rolling window. The blue line is the log price or return series, the black line is the corresponding Hurst exponent series, and the red line is the 0.5 threshold. Hurst exponent > 0.5, the series is momentum; Hurst exponent < 0.5, the series is mean reverting; Hurst exponent = 0.5, the series is random.

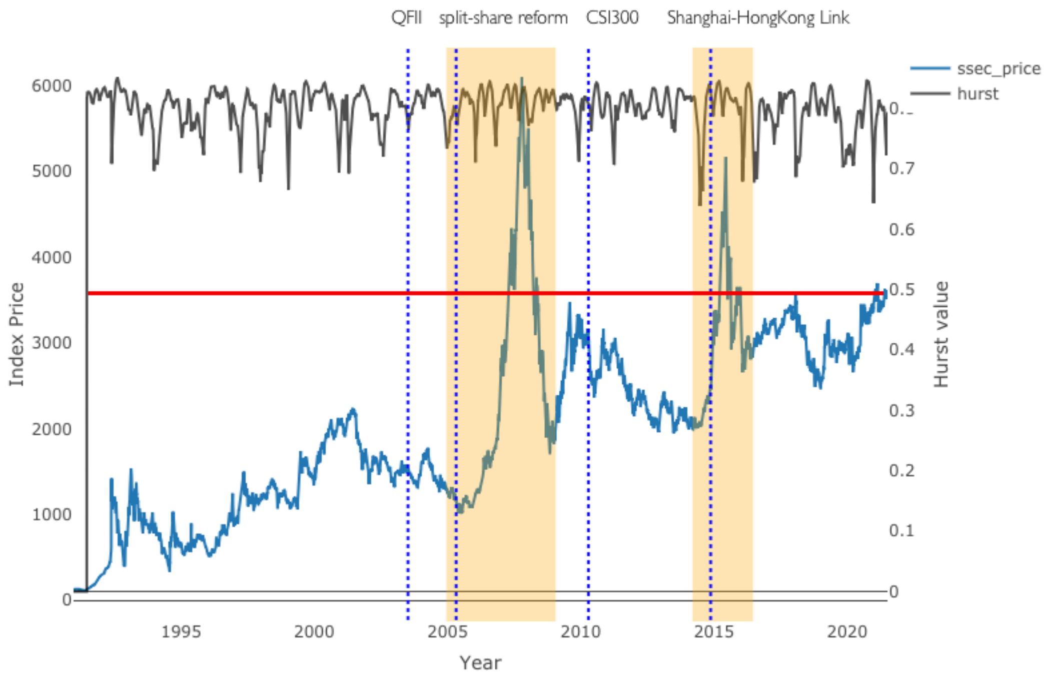

Figure 19.1 Hurst Exponent plots on SSEC price with 126 days rolling window

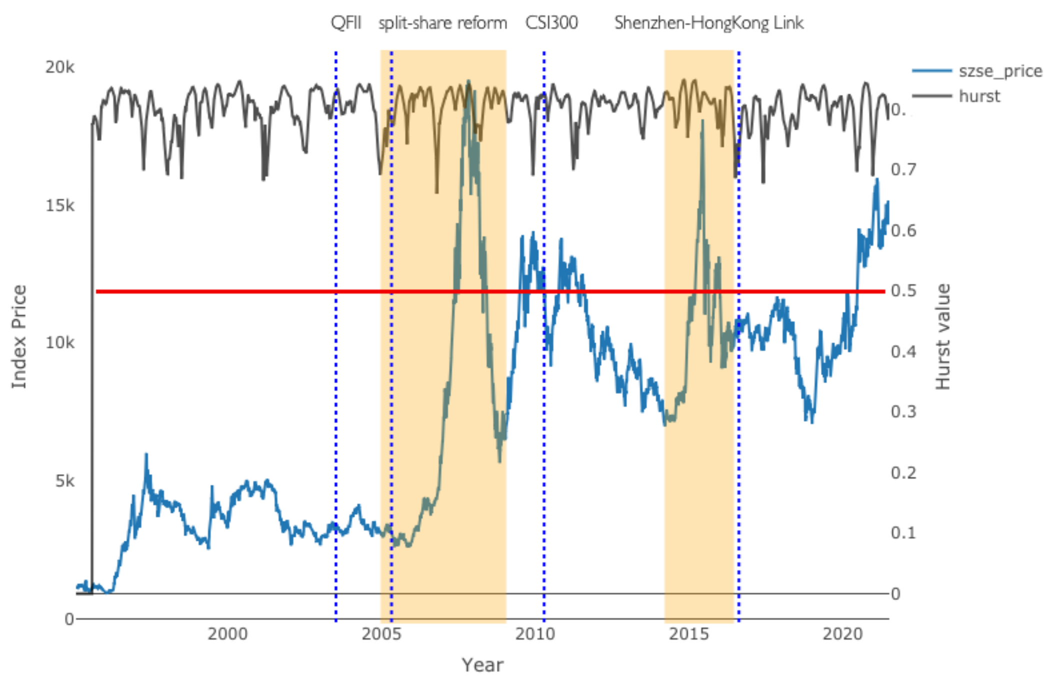

Figure 19.2 Hurst Exponent plots on SZSE price with 126 days rolling window

Figure 20. Hurst Exponent Tests Plots on SSEC and SZSE Return with rolling window N = 126

The following graphs from figure 20.1 and 20.2 represent the Hurst Exponent time series plots on returns of SSEC and SZSE with 126 days rolling window. The blue line is the log price or return series, the black line is the corresponding Hurst exponent series, and the red line is the 0.5 threshold. Hurst exponent > 0.5, the series is momentum; Hurst exponent < 0.5, the series is mean reverting; Hurst exponent = 0.5, the series is random.

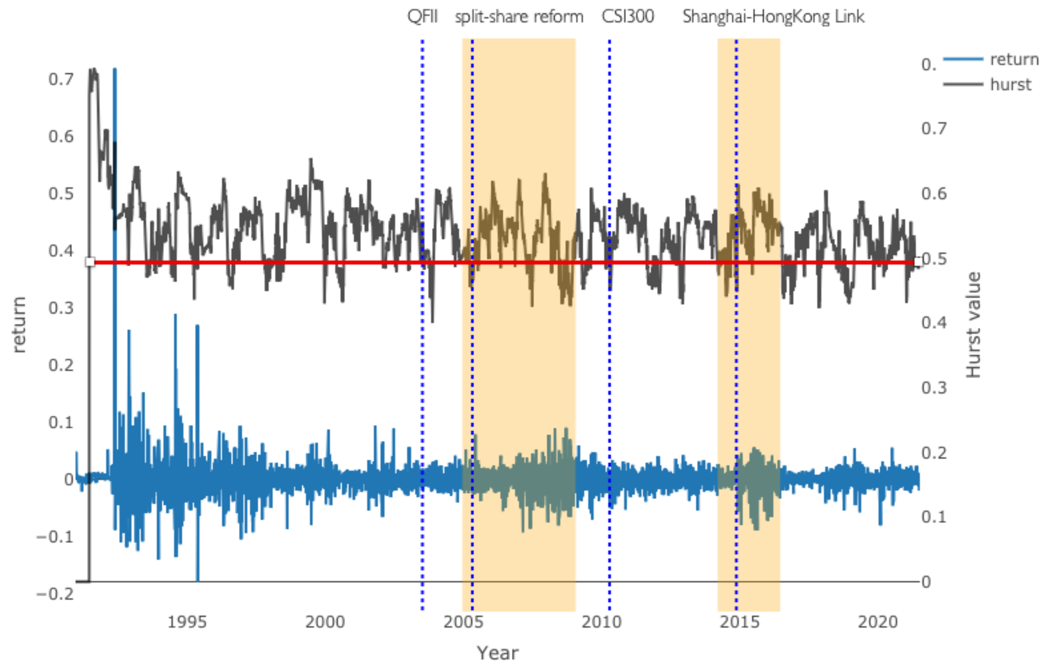

Figure 20.1 Hurst Exponent plots on SSEC return with 126 days rolling window

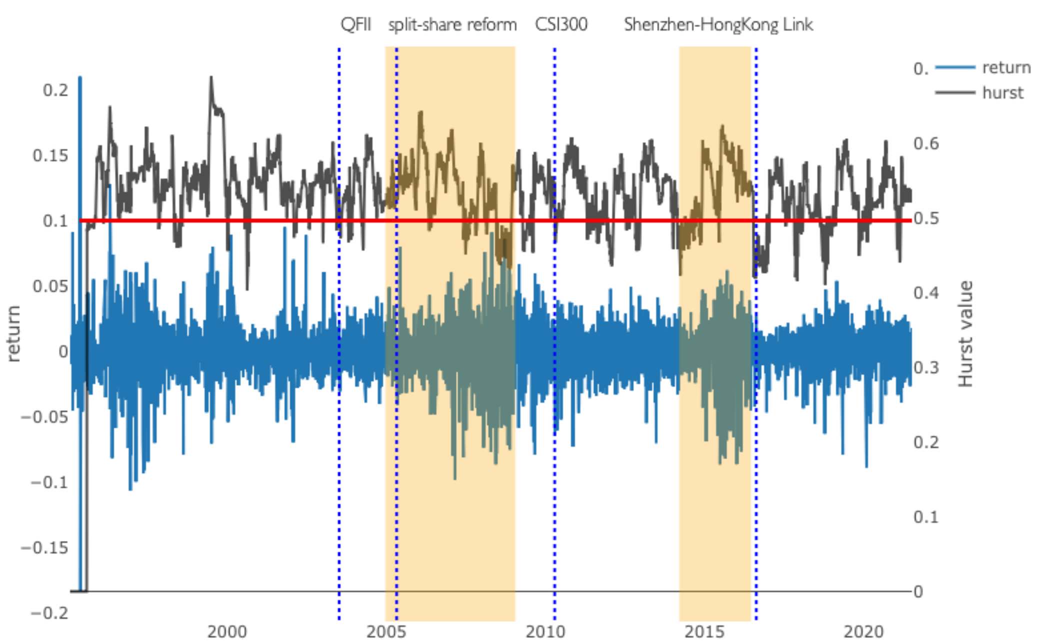

Figure 20.2. Hurst Exponent plots on SZSE return with 126 days rolling window

Below are tables displaying the results of traditional tests during periods of separated bull and bust.

Table 11a. Results of Ljung-Box test for SSEC's Separated Bull and Bust Period

This table provides the results of the Ljung-Box statistics in lag1, lag2, lag5, lag10, and lag30 of the daily returns on the SSEC for the separated bull and bust period

	Shanghai Index (SSEC)					
	sub-sample 2	sub-sample 2 bull	sub-sample2 bust	**sub-sample 4**	sub-sample 4 bull	sub-sample4 bust
	2005-01-04 to 2009-01-05	2005-01-04 to 2007-10-16	2007-10-17 to 2009-01-05	2014-04-01 to 2016-06-01	2014-04-01 to 2015-06-12	2015-06-13 to 2016-06-01
period	bull and bust period	first bull period	first bust period	bull and bust period	second bull period	second bust period
lag1	-0.004	-0.002	-0.038	0.075*	0.054	0.06
	(0.906)	(0.9593)	(0.5031)	(0.0826)	(0.3484)	(0.3515)
lag2	-0.022	-0.043	-0.038	-0.051	-0.079	-0.065
	(0.831)	(-0.5282)	(0.6421)	(0.1114)	(0.2534)	(0.3919)
lag5	0.007*	0.019	-0.046	0.006***	-0.084**	0.026
	(0.0783)	(-0.2545)	(0.6846)	(0.0063)	(0.039)	(0.2797)
lag10	0.009	0.009	-0.022	-0.110***	0.067	-0.19***
	(0.115)	(-0.1935)	(0.569)	(0.00027)	(0.1406)	(0.009)
lag30	-0.016***	-0.02**	-0.041	-0.072***	-0.085	-0.049***
	(0.0038)	(0.017)	(0.593)	(<0.00)	(0.2035)	(<0.00)

*** p<0.01, ** p<0.05, * p<0.1

Table 11b. Results of Ljung-Box test for SZSE's Separated Bull and Bust Period

This table provides the results of the Ljung-Box statistics in lag1, lag2, lag5, lag10, and lag30 of the daily returns on the SSEC for the separated bull and bust period

	Shenzhen Index (SZSE)					
	sub-sample 2	sub-sample 2 bull	sub-sample2 bust	**sub-sample 4**	sub-sample 4 bull	sub-sample 4 bust
	2006-01-04 to 2009-01-05	2006-01-04 to 2007-10-31	2007-11-01 to 2009--01-05	2014-04-01 to 2016-06-01	2014-04-01 to 2015-06-12	2015-06-13 to 2016-06-01
period	bull and bust period	first bull period	first bust period	bull and bust period	second bull period	second bust period
lag1	0.043	0.004	0.03	0.089**	0.046	0.087
	(0.2474)	(0.9244)	(0.6131)	(0.038)	(0.4254)	(0.1783)
lag2	-0.052	-0.061	-0.088	-0.015	-0.042	-0.023
	(0.1912)	(0.4357)	(0.2825)	(0.1113)	(0.5597)	(0.3786)
lag5	-0.009***	-0.003	-0.056	0.008*	-0.084	0.023
	(0.0085)	(0.4635)	(0.1521)	(0.084)	(0.4167)	(0.5238)

lag10	0.022**	0.002	-0.015	-0.167***	-0.018	-0.209*
	(0.0229)	(0.4216)	(0.2243)	(0.00)	(0.505)	(0.0523)
lag30	-0.017***	0.006	-0.059	-0.011***	-0.018	0.018**
	(0.0026)	(0.4874)	(0.1902)	(0.00)	(0.8081)	(0.042)

*** p<0.01, ** p<0.05, * p<0.1

Table 12a. Results of the Augmented Dickey-Fuller Unit Root Test for SSEC Index Price and Returns on Separated Bull and Bust Period

This table reports the results of the ADF unit root test to log prices of the Shanghai Composite Index and the first difference of price (return). The results displayed as without drift and time trend, with drift but without time trend, and with drift and time trend.

Shanghai Index (SSEC) Level						
	sub-sample 2	sub-sample 2 bull	sub-sample2 bust	**sub-sample 4**	sub-sample 4 bull	sub-sample4 bust
	2006-01-04 to 2009-01-05	2005-01-04 to 2007-10-16	2007-10-17 to 2009-01-05	2014-04-01 to 2016-06-01	2014-04-01 to 2015-06-12	2015-06-13 to 2016-06-01
period	bull and bust period	first bull period	first bust period	bull and bust period	second bull period	second bust period
None	0.56	3.81***	-2.49**	0.64	3.45***	-1.30
Intercept	-0.99	2.61*	-0.847	-1.57	1.64	-2.96**
	0.69	10.07***	3.37	1.47	7.14***	5.19**
Intercept and Trend	0.55	-1.28	-2.98	-0.97	-1.716	-3.27*
	1.37	8.96***	5.04**	1.09	6.6**	4.62*
	1.86	6.68**	4.48	1.39	4.02	6.1*
Shanghai Index (SSEC) Return						
None	-22.48***	-18.53***	-12.52***	-16.51***	-11.95***	-11.15***
Intercept	-22.49***	-19.09***	-12.88***	-16.51***	-12.72***	-11.25***
	252.81***	182.22***	82.99***	136.35***	80.85***	63.29***
Intercept and Trend	-22.6***	-19.59***	-12.866***	-16.59***	-13.06***	-11.34***
	170.18***	127.98***	55.19***	91.79***	56.85***	42.88***
	255.28***	191.96***	82.77***	137.68***	85.27***	64.30***

*** p<0.01, ** p<0.05, * p<0.1

Table 12b. Results of the Augmented Dickey-Fuller Unit Root Test for SZSE Index Price and Returns on Separated Bull and Bust Period

This table reports the results of the ADF unit root test to log prices of the Shenzhen Component Index and the first difference of price (return). The results displayed as without drift and time trend, with drift but without time trend, and with drift and time trend.

Shenzhen Index(SZSE) Level

	sub-sample 2	sub-sample 2 bull	sub-sample2 bust	**sub-sample 4**	sub-sample 4 bull	sub-sample4 bust
	2006-01-04 to 2009-01-05	2006-01-04 to 2007-10-31	2007-11-01 to 2009--01-05	2014-04-01 to 2016-06-01	2014-04-01 to 2015-06-12	2015-06-13 to 2016-06-01
period	bull and bust period	first bull period	first bust period	bull and bust period	second bull period	second bust period
None	1.01	4.28***	-2.03**	0.54	3.33***	-1.09
Intercept	-1.78	0.658	-0.84	-1.64	1.76	-3.22**
	2.22	9.19***	2.35	1.51	6.97***	5.75**
Intercept and Trend	0.09	-1.76	-2.39	-1.27	-1.41	-3.23*
	3.40	7.48***	3.26	1.02	6.17***	4.35*
	4.46	2.19	2.87	1.36	3.79	5.95*
Shanghai Index (SSEC) Return						
None	-19.68***	-14.81***	-12.59***	-15.84***	-11.62***	-10.59***
Intercept	-19.72***	-15.75**	-12.87***	-15.84***	-12.29***	-10.65***
	194.53***	123.96***	82.77***	125.53	75.49***	56.77***
Intercept and Trend	-20.10***	-15.79***	-12.84***	-15.88***	-12.64***	-10.74***
	134.69***	83.17***	55.01***	84.11***	53.26***	38.43***
	202.05***	124.76***	82.51***	126.16***	79.89***	57.63***

*** p<0.01, ** p<0.05, * p<0.1

Table 13a. Results of Runs Test for Shanghai Composite Index on Separated Bull and Bust Period

The table shows the results of the runs tests for SSEC on Separated Bull and Bust Period. This runs test used 0 as a threshold to calculate the days over or below 0. Total cases refer to the observations of each period and the number of runs sums up the positive runs and negative runs.

	Shanghai Index (SSEC)					
	sub-sample 2	sub-sample 2 bull	sub-sample2 bust	**sub-sample 4**	sub-sample 4 bull	sub-sample4 bust
	2005-01-04 to 2009-01-05	2005-01-04 to 2007-10-16	2007-10-17 to 2009-01-05	2014-04-01 to 2016-06-01	2014-04-01 to 2015-06-12	2015-06-13 to 2016-06-01
	bull and bust period	first bull period	first bust period	bull and bust period	second bull period	second bust period
Total Cases	972	672	300	532	295	237
Cases < 0	435	406	131	230	181	121
Cases >= 0	537	266	169	302	114	116
No of Runs	474	328	146	272	139	113
Z	-0.496	0.45	-0.3048	0.873	-0.233	1.765*
P-value	0.6196	0.6522	0.7605	0.3827	0.816	0.077

*** p<0.01, ** p<0.05, * p<0.1

Table 13b. Results of Runs Test for Shenzhen Component Index on Separated Bull and Bust Period

The table shows the results of the runs tests for SZSE on Separated Bull and Bust Period. This runs test used 0 as a threshold to calculate the days over or below 0. Total cases refer to the observations of each period and the number of runs sums up the positive runs and negative runs.

	Shenzhen Index(SZSE)					
	sub-sample 2	sub-sample 2 bull	sub-sample2 bust	**sub-sample 4**	sub-sample 4 bull	sub-sample4 bust
	2006-01-04 to 2009-01-05	2006-01-04 to 2007-10-31	2007-11-01 to 2009--01-05	2014-04-01 to 2016-06-01	2014-04-01 to 2015-06-12	2015-06-13 to 2016-06-01
	bull and bust period	first bull period	first bust period	bull and bust period	second bull period	second bust period
Total Cases	730	441	289	532	295	237
Cases < 0	320	279	131	239	168	125
Cases >= 0	410	162	158	293	127	112
No of Runs	341	211	130	275	147	128
Z	-1.46	0.515	-1.69*	0.942	0.16	1.157
P-value	0.1434	0.61	0.09	0.346	0.872	0.248

*** p<0.01, ** p<0.05, * p<0.1

Table 14a. Results of Variance Ratio Test on SSEC on Separated Bull and Bust Period

The table shows results of the variance ratio tests for returns on Shanghai Composite Index on the separated bull and bust period. The table report the variance ratio, VR(q) and the variance-ratio test statistics, Z(q) for homoscedastic increments and Z*(q) for heteroskedastic increments in parentheses for q = 2,4,8,16, which is the same q are used in Lo & Mackinlay (1988). The null hypothesis is that the variance ratios equal one and indicate the stock index return follow a random walk. Chow and Denning (1993) test results are also presented in the table. Lo- Mackinlay test assume to follow a normal distribution. The critical value is 1.65, 1.96 and 2.58 for 10%, 5% and 1% significant level. The critical values for Chow and Denning are 2.23, 2.49,3.02 for 10%, 5% and 1% significant level.

		Shanghai Index (SSEC)					
		sub-sample 2	sub-sample 2 bull	sub-sample2 bust	**sub-sample 4**	sub-sample 4 bull	sub-sample4 bust
		2006-01-04 to 2009-01-05	2005-01-04 to 2007-10-16	2007-10-17 to 2009-01-05	2014-04-01 to 2016-06-01	2014-04-01 to 2015-06-12	2015-06-13 to 2016-06-01
period		bull and bust period	first bull period	first bust period	bull and bust period	second bull period	second bust period
lag2	VR(q)	0.996	0.9967	0.959	1.075	1.054	1.059
	Z(q)	(-0.12)	(-0.087)	(-0.718)	(1.73)	(0.927)	(0.909)
	Z*(q)	(-0.09)	(-0.07)	(-0.642)	(1.17)	(0.844)	(0.7003)
lag4	VR(q)	1.0005	0.979	0.908	1.052	0.969	1.003
	Z(q)	(0.0009)	(-0.295)	(-0.848)	(0.64)	(-0.275)	(0.0269)

	Z*(q)	(0.007)	(-0.24)	(-0.808)	(0.43)	(-0.205)	(0.0207)
lag8	VR(q)	1.084	1.026	0.883	1.148	0.966	1.017
	Z(q)	(0.88)	（0.226）	(-0.685)	(1.16)	(-0.198)	(0.0893)
	Z*(q)	0.73	(0.185)	(-0.664)	(0.77)	(-0.148)	(0.0689)
lag16	VR(q)	1.19	1.129	0.737	1.229	1.009	0.822
	Z(q)	1.35	(0.759)	(-1.04)	(1.2)	(-0.036)	(-0.624)
	Z*(q)	1.13	(0.645)	(-1.009)	(0.84)	(0.028)	(-0.503)
chow-Denning	Z(q)	(1.36)	(0.759)	(1.036)	(1.73)	(0.927)	(1.32)
	Z*(q)	(1.12)	(0.645)	(1.009)	(1.17)	(0.844)	(1.15)

*** p<0.01, ** p<0.05, * p<0.1

Table 14b. Results of Variance Ratio Test on SZSE on Separated Bull and Bust Period

The table shows results of the variance ratio tests for returns on Shenzhen Component Index on the separated bull and bust period. The table report the variance ratio, VR(q) and the variance-ratio test statistics, Z(q) for homoscedastic increments and Z*(q) for heteroskedastic increments in parentheses for q = 2,4,8,16, which is the same q are used in Lo & Mackinlay (1988). The null hypothesis is that the variance ratios equal one and indicate the stock index return follow a random walk. Chow and Denning (1993) test results are also presented in the table. Lo- Mackinlay test assume to follow a normal distribution. The critical value is 1.65, 1.96 and 2.58 for 10%, 5% and 1% significant level. The critical values for Chow and Denning are 2.23, 2.49,3.02 for 10%, 5% and 1% significant level.

Shenzhen Index (SSEC)							
		sub-sample 2	sub-sample 2 bull	sub-sample 2 bust	**sub-sample 4**	sub-sample 4 bull	sub-sample 4 bust
		2006-01-04 to 2009-01-05	2006-01-04 to 2007-10-31	2007-11-01 to 2009--01-05	2014-04-01 to 2016-06-01	2014-04-01 to 2015-06-12	2015-06-13 to 2016-06-01
period		bull and bust period	first bull period	first bust period	bull and bust period	second bull period	second bust period
lag2	VR(q)	1.04	1.002	1.028	1.09	1.045	1.085
	Z(q)	(1.11)	(0.033)	(0.469)	(2.05**)	(0.772)	(1.321)
	Z*(q)	(0.95)	(0.026)	(0.439)	(1.47)	(0.659)	(1.149)
lag4	VR(q)	1.03	0.957	0.956	1.12	1.011	1.104
	Z(q)	(0.46)	(-0.478)	(-0.397)	(1.53)	(0.101)	(0.857)
	Z*(q)	(0.41)	(-0.389)	(-0.383)	(1.07)	(0.079)	(0.726)
lag8	VR(q)	1.14	0.979	0.966	1.26	1.013	1.198
	Z(q)	(1.28)	(-0.143)	(-0.193)	(2.01**)	(0.08)	(1.03)
	Z*(q)	(1.12)	(-0.119)	(-0.188)	(1.411)	(0.064)	(0.868)
lag16	VR(q)	1.25	0.938	0.877	1.36	1.052	1.049
	Z(q)	(1.55)	(-0.298)	(-0.476)	(1.88*)	(0.202)	(1.03)
	Z*(q)	(1.37)	(-0.257)	(-0.462)	(1.37)	(0.169)	(0.868)
	Z(q)	(1.55)	(0.478)	(0.476)	(2.05)	(0.772)	(1.32)

chow-Denning	Z*(q)	(1.37)	(0.389)	(0.462)	(1.47)	(0.659)	(1.15)

*** p<0.01, ** p<0.05, * p<0.1