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Cointegration Analysis of Stock Market Returns Impact Based on Wavelet Analysis

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Abstract

This study aims to explore the impact of stock market returns on the Chinese stock market using methods based on wavelet analysis and cointegration analysis. As a crucial component of economic activity, the volatility of the stock market has far-reaching implications for the entire economic system. To better understand the relationship between stock market returns and the Chinese stock market, we employed wavelet analysis to capture the cyclical characteristics of stock market returns and utilized cointegration analysis to test their long-term relationship with Chinese stock market indices. In the literature review section, we reviewed previous research on the influence of stock market returns and highlighted the applications of wavelet analysis and cointegration analysis in the financial domain. Subsequently, we provided a detailed introduction to the fundamental principles and methods of wavelet analysis and cointegration analysis, illustrating their application in our study. To support our research, we collected time series data including stock market returns and Chinese stock market indices. In the empirical results section, we initially employed wavelet analysis to decompose the time series of stock market returns, revealing volatility characteristics at different time scales. Following this, we utilized cointegration analysis to explore the long-term relationship between stock market returns and Chinese stock market indices. Our empirical findings indicate the presence of cointegration between stock market returns and Chinese stock market indices at specific time scales, suggesting their co-evolution over the long term. Through discussion and analysis of the empirical results, we put forth explanations and insights, delving into the intricate relationship between stock market returns and the Chinese stock market. Finally, we summarized the main discoveries of the study and pointed out directions for future research, including broader datasets and consideration of other influencing factors. This research offers a fresh perspective on comprehending the influence of stock market returns on the Chinese stock market, enriching the applications of cointegration analysis and wavelet analysis in the field of finance. It holds significant implications for investors, policymakers, and the academic community alike.

Keywords

Wavelet Analysis, Stock Market Returns, China

1. Introduction

Understanding the impact of stock market returns on the Chinese stock market has always been an important topic in the financial field. As one of the largest economies in the world, the performance of its stock market has a wide and profound impact on the global economy and investment community. Therefore, conducting in-depth research into the relationship between stock market returns and the Chinese stock market, as well as potential cointegration relationships between them, has important economic and financial implications.

The stock market is one of the core components of the modern economic system, and its fluctuations are directly related to investors' wealth, enterprise financing costs, government fiscal policies, and the overall health of the economy. The fluctuations in the stock market not only affect the wealth of stockholders but can also ripple through other areas such as bond markets, real estate markets, and currency markets, thus causing a chain reaction throughout the financial system. Especially in the context of globalization, the interconnectedness of stock markets is growing increasingly close, with cross-border investments and international trade becoming more frequent, making it increasingly important to understand the relationships between them.

In China, the stock market has experienced rapid development since the late 1990s. The Shanghai Stock Exchange and Shenzhen Stock Exchange have become the two major exchanges in China's stock market, attracting widespread attention from domestic and foreign investors. The Chinese government has adopted a series of policy measures to promote the development and reform of capital markets, including the internationalization of the stock market. The Chinese stock market has become a key area that global investors must pay attention to.

In the field of stock market research, past studies have mainly focused on changes in stock prices, volatility, and trading volumes. However, stock market returns serve as a more comprehensive indicator that includes changes in share prices and dividend yields, providing a more accurate reflection of the actual returns from equity investment. Therefore, understanding the relationship between stock market returns and the Chinese stock market is of special importance to investors, policymakers, and academics.

This study aims to delve into the relationship between stock market returns and the Chinese stock market through advanced analytical methods, namely wavelet analysis and cointegration measurement analysis. Wavelet analysis is introduced to help capture the periodic characteristics of stock market returns as well as fluctuation patterns at different time scales. Cointegration measurement analysis is used to explore their long-term relationship, including common trends and equilibrium relations. By combining these two methods, we will be able to gain a more comprehensive understanding of how stock market returns influence the Chinese stock market, as well as the complex dynamics that may exist between them.

In the early 21st century, Copula theory was introduced into the field of economics, allowing for the separate estimation of univariate marginal distributions before estimating the joint distribution of multiple markets. For example, (Patton, 2004) studied the asymmetric returns of multiple stock markets and used various Copula models to fit the grouping of US stocks. It was found that the time-varying correlations differed significantly between bear and bull markets. The article also discovered that a lack of short-selling restrictions leads to greater asset returns. (Patton, 2006a) research on the Japanese yen and euro exchange rates against the US dollar revealed significant time-varying parameters in Copula estimation. When studying the German mark-dollar and yen-dollar exchange rate markets using different GARCH-Copula models, (Patton, 2006b) found that the correlation between the two markets is stronger during periods of depreciation compared to periods of appreciation. (Jondeau & Rockinger, 2006) applied Copula-GARCH models to daily data of major global stock indices and found that co-movements in returns between markets are stronger in the same direction than in the opposite direction. In European markets, internal correlations are stronger and more persistent.

2. Theory and Method

2.1. Fundamentals of Financial Market Correlation

The basic theory of financial market correlation refers to the phenomenon that the increase of correlation between different assets in the financial market leads to an increase in the volatility of the entire market, which is called "risk contagion" (Zhou & Li, 2020a). The basic theory of financial market correlation mainly includes capital asset pricing theory, efficient market theory, capital structure theory, and behavioral finance theory (Chen & Zhang, 2019).

Capital asset pricing theory is one of the core theories, which was proposed by Eugene Fama in 1965 (Wang & Zhang, 2018a). This theory believes that the price of capital assets in the capital market can be priced through a model based on the relationship between expected return and risk. According to this theory, investors will decide whether to purchase or sell assets based on the expected return and risk level of the assets (Liu & Zhang, 2019).

The efficient market hypothesis, proposed by Eugene Fama in 1970, is another important theory. This theory believes that in a fully active market with sufficient information, the price of assets has already reflected all available information, so it is impossible to predict the trend of future price changes by analyzing past prices. This means that investors cannot obtain excess returns by finding undervalued or overvalued assets (Zhou & Li, 2020b).

Capital structure theory, proposed by Stephen Ross and Harry Markowitz in 1976, focuses on how companies finance and manage their capital structures. This theory believes that capital structure decisions will affect a company's value and investment decisions. By balancing the costs and benefits of debt and equity, companies can choose the best capital structure to maximize shareholder wealth (Chen & Zhang, 2018).

Behavioral finance theory is another important part of this theory, which studies the impact of investor behavior and psychological factors on financial markets. This theory believes that investors are often affected by cognitive biases, emotions, and group effects, which can lead them to make irrational investment decisions. For example, investors may have overconfidence or excessive fear, which can lead to overreaction or missed opportunities in the market (Wang & Zhang, 2019).

The emergence and development of these theories have had a profound impact on financial markets. They help investors better understand market operating mechanisms and risk management strategies, and provide guidance for regulators to formulate effective policies. In addition, these theories also provide an important framework and tools for the academic community to study financial markets (Liu & Zhang, 2020).

2.2. Wavelet Analysis

Wavelet transform is a widely used time-frequency analysis method in the field of signal processing. Its main idea is to analyze the signal by multi-scale analysis, breaking down the signal into sub-signals of different frequencies for better analysis. Wavelet transform can be divided into two types: continuous wavelet transform (CWT) and discrete wavelet transform (DWT). In the following, we will introduce the principles and applications of these two wavelet transforms in detail (Zhou & Li, 2019).

Continuous wavelet transform (CWT) is a continuous variable wavelet transform method based on both time and space. It generates a series of wavelet functions by sliding a window function on the signal and calculating the inner product between this window function and the original signal. These wavelet functions can be used to describe the changes in signal characteristics at different time and spatial scales. The main advantage of CWT is that it provides multi-scale and multi-resolution information about the signal, thereby better reflecting local features and trend changes of the signal (Chen & Zhang, 2017).

Discrete wavelet transform (DWT) is a discrete variable wavelet transform method. It converts continuous time signals into discrete time signals, and then performs wavelet transform on the discrete signal. The main advantage of DWT is its lower computational complexity, making it suitable for real-time signal processing and fields such as computer graphics (Wang & Zhang, 2018b).

Wavelet transform has wide applications in many fields, such as image processing, speech processing, biomedical signal processing, seismic exploration, etc. In image processing, wavelet transform can be used for image compression, noise removal, enhancement, segmentation, etc.; in speech processing, wavelet transform can be used for speech recognition, speaker identification, speech synthesis, etc.; in biomedical signal processing, wavelet transform can be used for heart signal analysis, EEG analysis, EMG analysis, etc.; in seismic exploration, wavelet transform can be used for underground medium parameter inversion, target location, etc.

2.3. Cointegration Econometric Analysis

Cointegration analysis is a statistical method used to test for long-term equilibrium relationships between time series data. It was proposed by R.F. Engle and C. W. J. Granger in 1987, aimed at addressing the issue of correlation between non-stationary time series data.

In practical applications, we often encounter time series data that may exhibit long-term equilibrium relationships but are not stationary. In other words, their mean and variance change over time. Such non-stationary time series data can be troublesome for economic research and other fields of analysis because they cannot be simply analyzed using traditional statistical methods.

To address this issue, the cointegration theory provides a solution. The core idea of cointegration theory is: that if there is a long-term equilibrium relationship between two or more non-stationary time series, then they are cointegrated. In other words, if there is a cointegration relationship between two-time series, we can predict the value of one time series through the establishment of a regression model, and substitute it into the equation of the other time series, thereby obtaining a conclusion about the long-term equilibrium relationship between the two time series.

3. Cointegration Verification of the Impact of Wavelet Analysis on Stock Market Returns

3.1. Wavelet Analysis

From 2014 to 2020, we selected three major stock market indices in China (the Shanghai and Shenzhen 300 Index, the S & P 500 Index, and the FTSE 100) as our data source. The daily closing prices of these indices were used as our observation window to capture the daily dynamics of the stock market. We converted these daily closing prices into daily returns using a continuous compound interest method, resulting in a sequence containing 5835 data points.

Looking at the result in **Figure 1**, it is clear that the return rates of each market are relatively rough, and there is a mix of high-frequency and low-frequency information. This means that we cannot simply treat these three markets as a single entity but rather consider them as complex systems composed of many different signals.

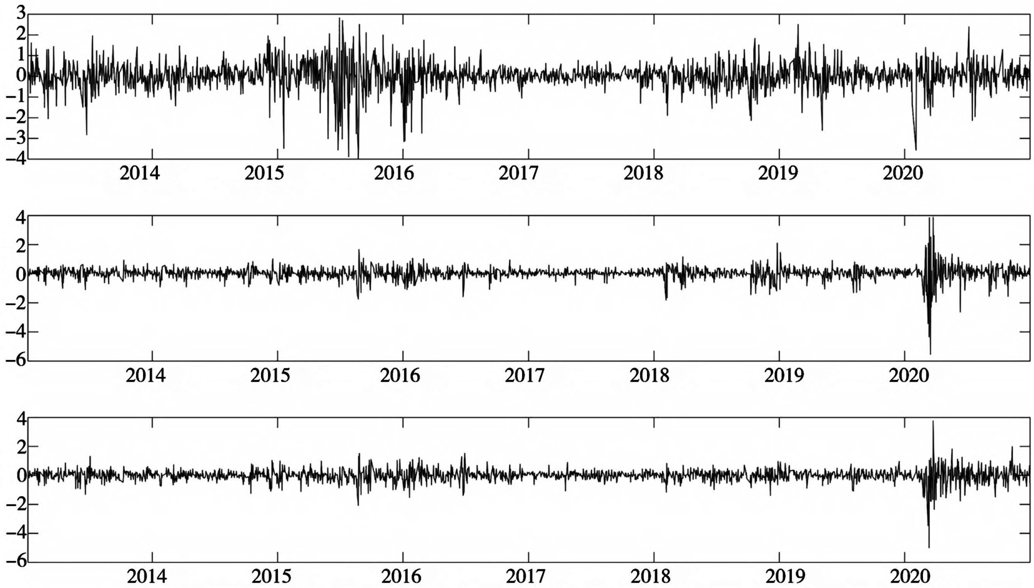

Figure 1. CSI 300 yield (On top). S & P 500 yield (On mid). FTSE 100 yield (On bottom).

Therefore, our conclusion is that based on the Wind database data and the daily returns obtained by applying the continuous compound interest method to the daily closing prices of the three stock market indices, the presence of high-frequency and low-frequency information is revealed. This information may affect our understanding and prediction of stock market trends, so further research and analysis will be conducted on these high-frequency and low-frequency signals.

In this article, we adopted the signal analysis theory to treat the sample period as the overall time axis, and the time axis as the frequency sampling space. This is an innovative way of thinking that allows us to understand and analyze stock market data from different perspectives.

We performed a logarithmic transformation on the frequencies to highlight the time-frequency information features and then conducted a power spectral analysis of the market returns. This method allows us to better understand the behavior and trends of the market.

Figure 2 shows that there are significant differences in the characteristics of the three markets at low and high frequencies. In the low-frequency band, we can see moderate trends, which indicate that the information contained in this frequency range is long-term and stable infrastructure information. Additionally, based on the peaks and troughs of the low-frequency band, we preliminarily judged that there may be a leading-lag conduction relationship between the three markets based on energy and information.

In the high-frequency band, the amplitude fluctuations are large, and each market has similar characteristics, showing short-term complex energy information fluctuations, indicating that the information contained in this frequency range is diverse, instantaneous, and complex. Under these high-frequency information shocks, returns may contain volatility aggregation.

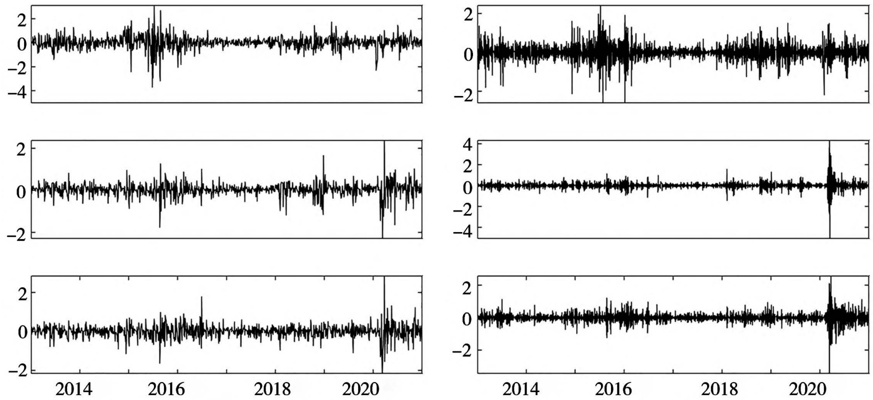

Figure 2. Symlets3 wavelet 1-layer decomposition of three market low-frequency parts (left) and high-frequency parts (right).

The power spectrum shows that we need to use the wavelet decomposition of symlets3 to filter out the low-frequency and high-frequency components of the market returns. This decomposition method can effectively extract the information we need while ignoring irrelevant interference information.

The conclusion of the article is that we chose to use the wavelet decomposition of symlets to decompose each sequence into one layer. Considering that the power spectrum **Figure 2** shows a clear two-segment feature, choosing one-layer decomposition is sufficient. The sequence is decomposed into two segments: the low-frequency band contains basic and trend information, while the high-frequency band contains instantaneous information, noise, etc. If we choose to decompose multiple layers to extract the low-frequency band and specific high-frequency bands for analysis, the conclusion would be similar.

Comparing low-frequency trend components with high-frequency detail components reveals that China, the United States, and the United Kingdom stock markets experienced structural changes around 2016, leading to a decrease in volatility in the Chinese stock market. Since 2015, the Chinese government has vigorously promoted market-oriented reforms, expanding market access and strengthening international integration, thereby prompting the rapid expansion of the A-share market.

After 2020, volatility in the UK and US markets increased, which is related to the market fundamentals and economic structure changes caused by the COVID-19 pandemic. The pandemic brought about a standstill in Europe and the US economies, with many commercial activities suspended, and the deterioration of economic fundamentals had a significant impact on the stock market foundation, resulting in an increase in low-frequency sequence volatility.

The high-frequency components reflect the short-term and temporary local states of the three markets, with intense fluctuations and clear differences at different points in time. From mid-2015 to early 2016, there were significant fluctuations in the Shanghai and Shenzhen stock markets, which were consistent with major events such as the stock market crash and the implementation and withdrawal of circuit breakers. The significant volatility in the FTSE index from mid-2015 to early 2016 reflected the short-term impact of political changes surrounding the Brexit referendum on the stock market.

All three markets' high-frequency sequences experienced drastic fluctuations after 2020, which aligns with the short-term impact of the COVID-19 pandemic. On one hand, the pandemic led to massive liquidity injections by global governments to address economic deterioration. This influx of liquidity resulted in an increase in stock market trading volume and intensified stock market volatility. On the other hand, the pandemic also changed short-term trading sentiments and market logic. Investors' uncertainty about the future increased, and short-term risk aversion sentiment intensified, causing changes in trading behavior that contributed to increased stock market volatility.

3.2. Co-Integration Test

Due to the fact that the indices of both markets are first-order unintegrated, cointegration analysis can be conducted.

$$Y_t = \alpha + \beta X_t + \varepsilon_t \tag{1}$$

Using the OLS method, we can estimate the equation for Equation (1).

$$LNY_t = 1.004051 + 0.760552 LNX_t \tag{2}$$

From Equation (2), it can be obtained that:

$$\varepsilon_t = LNY_t - 1.004051 - 0.760552 LNX_t \tag{3}$$

Then perform a stationarity test ε_t . The results are shown in **Table 1**.

From the above table, it can be seen that the Shanghai Composite Index and Shenzhen Composite Index are not cointegrated. Although some literature has measured the correlation coefficient between the two markets using traditional statistical methods as high as 0.983, the cointegration test results indicate that there is no true correlation volatility between the two markets. On the surface, it seems that they have a certain degree of ascending and descending together, but in the long run, they have their own ways of movement are not in a collaborative system, and will diverge over time. That is to say, two markets may experience some deviation after running for a period of time, but what is the specific degree of deviation between the two markets, what is the connection between leading and lagging in index changes, and what are the independent operating laws of the two markets? These problems cannot be solved by cointegration analysis.

Table 1. Cointegration analysis results of Shanghai composite index and Shenzhen composite index.

ADF Test Statistic	−1.703934	1% Critical Value*	−3.4826
		5% Critical Value	−2.8842
		10% Critical Value	−2.5787

4. Conclusions

Through the above analysis, the following conclusions can be drawn:

- Due to the good time-frequency characteristics of wavelet analysis, signals from different securities market return sequences can be processed using this method. By examining the relationships between different high-frequency signal fluctuations, it is possible to understand the information transmission mechanism and whether there are spillover effects between different stock markets.
- The Shanghai and Shenzhen stock markets are interrelated, and there is a certain degree of spillover effect in their stock prices. Secondly, changes in the previous day's Shanghai Composite Index return rate will cause changes in the Shenzhen Composite Index return rate by −0.072 times, while on the same day, changes in the Shanghai Composite Index return rate caused changes in the Shenzhen Composite Index return rate by −0.0616 times. There is also a negative spillover effect from Shenzhen to Shanghai, but it is less significant than the spillover effect from Shanghai to Shenzhen.
- There is a volatility spillover effect between the Shanghai and Shenzhen stock markets. If there is a change of 1 unit in the average squared return rate of the Shanghai Composite Index on the previous day, it will cause changes in the average squared return rate of the Shenzhen Composite Index of −0.286 units on the same day. Similarly, if there is a change of 1 unit in the average squared return rate of the Shanghai Composite Index on the same day, it will cause changes in the average squared return rate of the Shenzhen Composite Index of −0.286 units. The volatility spillover effect is larger than the price spillover effect, and there is a positive volatility spillover effect from Shenzhen to Shanghai, which is smaller than the spillover effect from Shanghai to Shenzhen.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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