The Impact of Events on Long-Term Persistence of Global Stock Markets: Evidence from the CSI 300, HSI, and S&P 500

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Abstract. This study takes the daily return series of the CSI 300 Index, HSI, and S&P 500 Index as the research object, investigating the changes in the long-term behavior persistence of global stock markets in response to major events. Using the ARFIMA model to estimate long-memory parameters and the Bai-Perron method to detect structural breaks, the results shows that long memory increases during periods of structural breaks, indicating reduced market efficiency. Further analysis reveals that the changes in the long-term behavior of global stock markets are not independent but are characterized by significant cross-market linkages. Specifically, major shocks such as financial crises, policy adjustments, natural disasters, and public health events not only induce structural breaks in individual markets but also lead to synchronized movements in global stock markets.

Keywords: Long-term behavior, Long memory, Structural breaks, ARFIMA.

1 Introduction

The long-term behavior of stock markets reflects overall trends and price fluctuations over extended periods, influenced by economic factors, policy changes, and structural shifts. As financial markets grow more complex, understanding the persistence of long-term market behavior has become crucial.

Long memory, first introduced by Ding and Granger (1993) [1], is a key measure of market persistence, where past price movements influence future prices. Studies have shown that long memory exists in stock returns and volatility, with Hull and McGroarty (2014) [2] observing it in stock market volatility, and Ferreira and Dionísio (2016) [3] in the U.S. markets. However, the effect tends to be short-lived due to efficient price adjustments. In emerging markets, Kasman et al. (2009) [4] found stronger long memory, attributed to market inefficiencies, while Tan et al. (2022) [5] noted more pronounced long memory in Chinese markets due to unique structures and regulatory interventions.

M. Zhang et al. (eds.), *Proceedings of the 2025 5th International Conference on Informatization Economic Development and Management (IEDM 2025)*, Advances in Economics, Business and Management Research 330,
https://doi.org/10.2991/978-94-6463-724-3_10

Global economic events disrupt market persistence and cause structural breaks, altering long-term behavior. For instance, the 2015 Chinese stock market crash and the 2020 COVID-19 pandemic triggered volatility spikes. Studies by Raheel Asif (2022) [6], Ghosh, B., & Bouri, E. (2022) [7], and Ndako (2022) [8] found that such events often lead to market instability. Guedes (2022) [9] observed increased long memory in G20 economies following major shocks, while Tan et al. (2024) [10] used long-memory and structural break models to analyze U.S. and Chinese markets.

While much research has focused on modeling stock returns and volatility, few studies examine how major events and structural breaks affect long-term market behavior. Key questions remain: Which events have the most profound impact on markets? Does long-term market behavior persist globally? Can significant events reshape market dynamics?

This study focuses on the CSI 300, HSI, and S&P 500 indices, representing the financial markets of China mainland, Hong Kong, and the U.S. The Bai-Perron method is used to detect structural breaks, and the ARFIMA model estimates long-memory parameters. The study provides empirical evidence that major events, such as financial crises, policy adjustments, natural disasters, and public health events, cause synchronized long-term behavior and structural breaks in multiple markets, revealing the increasing interconnectedness of financial markets.

2 Data and Methodology

This study analyzes three major stock indices: the CSI 300, HSI, and S&P 500. The CSI 300 represents China's A-share market, reflecting overall trends and volatility. The HSI is a key indicator of Hong Kong's stock market, sensitive to global economic and policy shifts. The S&P 500 serves as a benchmark for the U.S. market, with fluctuations impacting global financial markets. These indices provide an international perspective on market performance under external shocks. The dataset covers daily closing prices from January 4, 2005, to September 13, 2024 (4,523 trading days), including major crises such as the 2008 global recession and the 2020 COVID-19 pandemic, sourced from the Wind Database. Logarithmic returns were calculated from the difference in consecutive daily log closing prices.

To explore long memory in stock returns, this study employs the Auto-Regressive Fractionally Integrated Moving Average (ARFIMA) model, proposed by Granger and Joyeux (1980) and Hosking (1981). The model accounts for fractional integration, with the long-memory parameter d indicating persistence.

$$\phi(B)y_t = \theta(B)(1-B)^{-d}\varepsilon_t \tag{1}$$

Where: $\phi(B) = 1 + \phi_1 B + \cdots + \phi_1 B^P$, $\theta(B) = 1 + \theta_1 B + \cdots + \theta_q B^q$ are the autoregressive and moving average operators, respectively. $(1-B)^{-d}$ represents the fractional differencing operator expanded using a binomial series.

When $d = 0$, the logarithmic return series is stationary with no long-term dependence. If $0 < d < 0.5$, the series exhibits strong long-memory, where past values significantly impact future returns. Conversely, if $-0.5 < d < 0$, the process shows moderate memory or anti-persistence, where positive and negative returns alternate, reducing long-term dependence.

Structural breakpoints can significantly affect market performance. Therefore, the Bai and Perron (2003)[11] structural breakpoint detection method is used to identify these breakpoints. The testing process is as follows:

Consider a linear regression model with m breakpoints dividing the series into m+1 segments:

$$y_t = x_t\beta + z_t\delta_j + u_t \tag{2}$$

Where y_t represents the dependent variable, x_t and z_t represent vectors of explanatory variables, respectively, β and δ_j are the corresponding parameter vectors, and u_t denotes the error term. When $\beta \neq 0$, it indicates that only some parameters change with the structural break, forming a partial structural change model. If $\beta = 0$, it indicates that all parameters change, resulting in a pure structural change model.

In the process of studying structural breakpoints, we first use the UD_{max} and WD_{max} statistics to determine whether structural breakpoints exist. If structural breakpoints are detected, the $sup\ F$ test and the dynamic programming method are then applied to identify the specific number and locations of the breakpoints.

3 Empirical Analysis

This study explores how global stock markets respond to major events and how these events cause structural changes that affect long-term market behavior. By identifying structural breaks in key indices during significant events, we gain insights into market dynamics and their potential future impact. Using the Bai-Perron breakpoint analysis and the ARFIMA model, this section examines how these events influence the long memory characteristics of return series. The findings offer empirical support for understanding the persistence of long-term behavior in global markets.

3.1 Analysis of Structural Breakpoints in the Three Major Stock Indices

This section uses the Bai-Perron method to identify potential structural breakpoints in the CSI 300, HSI, and S&P 500 indices. Table 1 lists the breakpoints and corresponding events. A comparison reveals that breakpoints lack clear periodicity, ruling out cyclical influences, and typically correspond to significant domestic or international events, often with a delayed impact.

Table 1. Major Events Corresponding to Structural Breakpoints in Stock Markets

Stock	Date	Event Description
S&P 500	06/7/17	U.S. housing market slowdown and rapid rise in subprime mortgages
	07/10/15	Bankruptcy of two Bear Stearns hedge funds
	08/3/19	JPMorgan acquires Bear Stearns
	08/9/2	Bankruptcy of Lehman Brothers
	09/3/5	$787 billion U.S. economic stimulus plan

	11/9/23	"Occupy Wall Street" movement breaks out
	18/8/6	U.S.–China trade war
	20/3/18	Outbreak of the COVID-19 pandemic
CSI 300	07/10/15	17th National Congress of the Communist Party of China convened
	08/5/19	Wenchuan Earthquake
	08/10/29	Global financial crisis
	10/7/5	Issuance of Agricultural Bank of China IPO
	15/6/8	Stock market crash triggered by margin financing collapse
	16/1/29	Introduction of the "circuit breaker" system
	18/10/18	U.S.–China trade friction
	20/3/19	Outbreak of the COVID-19 pandemic
	21/2/9	Continuation of U.S. bond market rally
HSI	07/10/30	First batch of institutional investors' funds flows into the HK market
	08/5/20	Wenchuan Earthquake
	08/11/20	Global financial crisis
	09/7/31	First round of U.S.-China strategic and economic dialogues
	15/5/26	Margin financing collapse triggers a "stock crash"
	19/4/17	Hong Kong social events
	20/3/23	Outbreak of the COVID-19 pandemic
	22/2/16	Outbreak of the fifth wave of the pandemic
	22/10/25	"Policy Statement on Developing Hong Kong's Virtual Assets"

3.2 Characteristics of Price Movements and Market Efficiency under Structural Breakpoints in the Three Major Stock Indices

Structural breakpoints in stock markets impact the persistence of long-term behavior. This section uses the ARFIMA model to analyze how these events influence market persistence and efficiency.

Long memory refers to the impact of past returns on future prices, while market efficiency suggests that prices fully reflect available information. A long-memory parameter of zero indicates an efficient market, where returns follow a random walk, while a significant deviation from zero suggests inefficiency. The closer the long-memory parameter is to zero, the higher the market efficiency. Table 2 presents the long-memory parameters (d) for the three indices, segmented by structural breakpoints, to assess market efficiency at different stages.

Table 2. Changes in Market Efficiency Across Different Phases for the Three Stock Markets

	CSI 300 Index		HSI		S&P 500 Index	
Period	d	Efficiency	d	Efficiency	d	Efficiency
05/1/1~07/10/15	0.077	Inefficient	0.054	Inefficient	-0.007	Efficient
07/10/15~08/9/15	0.065	Inefficient	0.167	Inefficient	0.040	Efficient
08/9/15~09/3/5	0.085	Inefficient	0.147	Inefficient	-0.068	Inefficient
09/3/5~20/3/11	0.092	Inefficient	0.115	Inefficient	0.074	Inefficient
20/3/11~24/9/13	0.103	Inefficient	0.089	Inefficient	0.057	Inefficient
Full Sample	0.091	Inefficient	0.106	Inefficient	0.049	Efficient

Global capital flows, policy changes, and economic shifts have led to greater market integration. From 2005 to July 2007, during global economic expansion, all three markets rose together. The CSI 300 and HSI exhibited positive long-memory, indicating low market efficiency due to weak regulation in China, while the S&P 500 showed nearly zero long-memory, reflecting high efficiency. Despite different efficiencies, global capital flows aligned their price trends.

In August 2007, the subprime mortgage crisis triggered structural breakpoints in all three indices. The HSI's long memory increased significantly, while the CSI 300 maintained high long memory. After the 2008 Lehman Brothers bankruptcy, all markets experienced crashes, with the CSI 300 showing further increased long memory, while the S&P 500 exhibited negative long memory. After the financial crisis, global markets recovered in sync, supported by government interventions. In 2009, U.S. fiscal stimulus and quantitative easing triggered a recovery, with synchronized market growth and increased long memory in the CSI 300 and S&P 500, though all markets remained weakly efficient. The COVID-19 pandemic in 2020 caused sharp declines, with the CSI 300's long memory rising to 0.10, while the HSI and S&P 500 showed reduced long memory, though inefficiency persisted.

The COVID-19 pandemic in March 2020 marked another breakpoint, causing sharp declines in global markets. The CSI 300's long memory increased to 0.10, while the HSI and S&P 500 exhibited reduced long memory compared to the financial crisis, though all markets remained inefficient. Gradual recovery followed, supported by large-scale government interventions. Table 2 provides the long-memory parameters of the three indices segmented by structural breakpoints.

In conclusion, major events significantly impact long-memory characteristics. The CSI 300 shows persistent long memory, while the HSI's long memory strengthens under shocks. The S&P 500, initially efficient, saw reduced efficiency during the financial crisis. Furthermore, this study also uses the R/S analysis method to estimate the Hurst exponent, verifying the robustness of the results. The estimation results from the R/S analysis are very close to the previous results.

4 Conclusions and Policy Recommendations

This study shows that major global events, like the financial crisis and COVID-19, significantly impact long-term market behavior. All three indices display clear structural breakpoints linked to key events. During periods of significant structural changes, long memory in all three markets increased significantly. The CSI 300 and HSI exhibited high long-memory levels, indicating reduced market efficiency, while market behavior during these phases was non-persistent. The global financial crisis and COVID-19 pandemic saw synchronized changes in long memory across the three indices, reflecting deeper globalization and stronger interdependence among capital markets. These findings indicate that long memory increases during structural breaks, and the long-term behavior of global stock markets is interconnected, with significant cross-market linkages.

Financial institutions should incorporate long-memory models into their risk assessment frameworks and use scenario analysis to evaluate cross-market risks. Regulators should strengthen international cooperation by establishing global regulatory coordination mechanisms. This could involve sharing information with other countries and international organizations, such as the International Monetary Fund, International Organization of Securities Commissions, and aligning standards and policies. For example, a cross-border regulatory framework for multinational financial institutions should be developed.

Acknowledgments

The research is financially supported by the National Social Science Fund of China (Grant no: 20BTJ042) and the Fundamental Research Funds for the Central Universities.

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