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Original Paper

Research on the Linkage between Chinese and American Stock Markets

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Abstract

This article selects the VAR model to explore the performance linkage between Chinese and American stock markets. Firstly, this article selects the Shanghai and Shenzhen 300 Index and the Dow Jones Index as representative variables of the Chinese and American stock markets, uses daily data from March 1, 2017 to December 29, 2023 to construct and estimate VAR models, conduct model estimation, and analyze impulse responses. Finally, it concludes that there is a lag effect linkage between Chinese and American stock markets, with both indices showing positive volatility. The Dow Jones Index has a positive impact on the Shanghai and Shenzhen 300 Index, and vice versa. Based on this conclusion, it suggests that when formulating cross-border investment and risk management strategies, one should consider the impact of significant events affecting both Chinese and American stock markets.

Keywords

VAR model, CSI 300 Index, Dow Jones Index, impulse response function

1. Introduction

Deepening globalization has tightened the web of connections among national economies and financial markets. Cross-border trade, capital flows and the global footprint of multinational firms have steadily increased the co-movement of stock markets worldwide. Against this backdrop, the relationship between the equity markets of China and the United States—the world's two largest economies—has attracted intense scrutiny.

China's economic and financial ascent began with the reform and opening-up policies launched in 1978. Gradual liberalization—ranging from the relaxation of price controls to the encouragement of private enterprise—culminated in the founding of the Shanghai and Shenzhen stock exchanges in 1990, marking the formal birth of the country's modern capital markets. As China opened further, foreign capital poured in, accelerating the capitalization of its economy. Yet frequent trade interactions with the United States also bred friction, culminating in a protracted trade dispute that saw Washington launch tariff investigations and impose duties on Chinese goods.

The Chinese stock market was first rattled by the COVID-19 shock, but aggressive government intervention and early signs of an economic rebound soon powered a sharp A-share rally. In contrast, the Dow Jones Industrial Average slumped under the combined weight of a global pandemic and the 2020 oil-price war. By late 2022, China's sudden exit from its zero-COVID regime ended three years of strict containment, yet the expected post-pandemic surge in domestic equities did not materialize. The Shanghai Composite closed 2023 at 2,975, down 114 points or 3.7 % from the prior year-end; the Shenzhen Component finished at 9,525, off 1,491 points or 13.5 %. After an encouraging start to the year, the A-share rally fizzled in May, and the market repeatedly tested levels below the psychologically important 3,000 mark. Early optimism about a swift recovery and robust policy support gave way to deepening investor anxiety over growth prospects and corporate earnings.

Across the Pacific, Wall Street told a different story. The Dow closed 2023 at 37,689—up 4,532 points, or 13.7 %, from 33,147 a year earlier. The United States had lifted pandemic restrictions earlier, allowing a longer runway for recovery. Solid macro indicators—improving payroll numbers, rebounding corporate profits and resilient consumer spending—underpinned investor confidence and propelled the market upward.

Even after the trade war and the pandemic, the performance of Chinese and U.S. equities has remained intertwined. Their co-movement is more than a statistical curiosity; it is a barometer of cross-border economic linkages and risk transmission. When the two markets swing in tandem, the common drivers often include synchronized macro factors, spillovers from policy shifts or shifts in global risk appetite. Understanding this linkage not only illuminates the mutual dependence of the world's two largest economies but also equips economists and policymakers with insights needed to craft domestic strategies that account for external shocks and spillovers.

2. Literature Review

Over the past two decades, the literature on China–U.S. stock-market linkages has grown rapidly. Early studies focused primarily on measuring unconditional correlations or cointegration relationships. More recent work has shifted toward dynamic features: time-varying correlations, volatility spill-overs, contagion effects, and regime-dependent changes—especially during the global financial crisis (GFC), the U.S.–China trade war, and the COVID-19 pandemic.

2.1 International Evidence

Arshanapalli et al. (1993) use newly developed cointegration techniques to test for international stock-price co-movements. After the October 1987 crash, they document a sharp rise in cross-market integration, the Nikkei being the only major index left outside the cointegrated system.Ang & Bekaert (2002) embed regime-switching processes in portfolio-choice models and show that policy regime changes raise the risk of international equity allocations, thereby altering cross-market correlations. Chan et al. (2010) apply a Markov-switching framework to equity, commodity, and real-estate returns and highlight significant inter-asset linkages that must be considered when assessing diversification benefits. Engsted and Tanggaard (2004) decompose U.S. and U.K. stock-return variance via a VAR and find that news about future dividends, real rates, and excess returns drive the high positive correlation between the two markets. Their evidence rejects the simple present-value model advocated by Beltratti and Shiller (1993). Chen et al. (2006) employ a Fractionally Integrated VECM (FIVECM) on India–U.S., China–U.S., and India–China pairs. The U.S. dominates first-moment linkages, whereas China dominates second-moment feedback. Palamalai and Murugesan (2013) use cointegration and VECM techniques on Asia-Pacific emerging markets. They confirm long-run equilibrium relationships and short-run diversification opportunities. Ye (2014) shows that, despite non-overlapping trading hours, the sign of the overnight U.S. return (S&P 500 or DJIA) reliably predicts the direction of the next-day open in China (SSE or SZCI), a pattern that has strengthened since 2006. Singh et al. (2015) combine a trivariate VAR with TGARCH to study the 2007–09 sub-prime crisis. U.S. returns Granger-cause Indian and Chinese returns, and volatility spills from the United States to India and then to China. The cross-market volatility impact fades over time, largely due to past shocks and leverage effects.Caporale et al. (2021) document long memory in all major indices and show that ASEAN-5 banking sectors are more integrated with China than with the United States. The 2008 GFC and the 2015 Chinese stock-market crash significantly altered these integration patterns, whereas the COVID-19 shock weakened the overall China–ASEAN linkage.

2.2 Domestic (Chinese) Evidence

Zhang et al. (2004) test for cointegration and Granger causality between China's and the U.S. markets. Before 19 February 2001—when China opened its B-share market to domestic investors—no cointegration was detected; afterward, both returns and volatility began to converge, implying a long-run relationship. Han and Tian (2005) adopt an MA(1)-GARCH(1,1)-M model and find that the U.S. close has no predictive power for the Chinese open. They nevertheless argue that deepening Sino-U.S. trade will gradually strengthen the linkage. Gong Pu et al. (2009) estimate a time-varying t-Copula and show that shocks originating in the United States reach mainland China via Hong Kong, amplifying volatility in A-shares. Zhang et al. (2010) demonstrate that the QDII (Qualified Domestic Institutional Investor) program—introduced after China's WTO entry—created a cointegrated relationship between the two markets. During extreme events such as the GFC, U.S. shocks propagated to China more forcefully. Yang Xuelai et al. (2012) embed macro factors and regime shifts in a DCC-GARCH model and attribute the surge in China–U.S. correlation during the GFC to structural breaks in U.S. monetary policy. Gong et al. (2015) use non-parametric volatility measures to show that rising Sino-U.S. trade intensity—not financial liberalization per se—drives the increase in co-movement; paradoxically, gradual liberalization actually dampens the linkage.Yin Zhichao et al. (2020) apply an event-study methodology to seven key trade-war announcements. They document significant negative spill-overs to Chinese stocks; negative shocks last longer than positive ones. Wang et al. (2021) estimate a VAR-GARCH-BEKK (1,1) model across subsamples and conclude that the bilateral volatility spill-over during COVID-19 is the strongest observed since the 2008 GFC, the 2015 crash, or the 2018 tariff dispute.

This paper builds on and complements the above literature by re-examining the complex, time-varying interactions between the Chinese and U.S. equity markets. Using a VAR framework and impulse-response analysis, we quantify how shocks originating in one market propagate to the other, thereby updating our understanding of cross-border risk transmission in the post-pandemic era.

3.Theoretical Framework and Hypotheses

3.1 Efficient-Market Hypothesis (EMH)

The EMH posits that asset prices fully and instantaneously incorporate all available information. Applied to China–U.S. equity linkages, any material news emanating from the United States—macroeconomic releases, earnings surprises, or policy shifts—should be rapidly impounded into global prices, including Chinese stocks. Because Chinese and international investors now monitor U.S. markets in real time, the information channel tightens and cross-market correlation rises.

Globalization further amplifies this mechanism. The growing participation of Chinese institutions in U.S. markets and the operation of Stock Connect programs (Shanghai–Hong Kong, Shenzhen–Hong Kong) facilitate instantaneous capital reallocation. A rally on Wall Street, for example, can lift risk appetite among Chinese investors and attract north-bound flows, reinforcing co-movement. Finally, synchronized macro drivers—interest rates, inflation expectations, trade policy—produce common shocks that both markets must discount. Under EMH, these joint fundamentals generate stronger and faster cross-market feedback loops.

3.2 Cointegration Theory

Cointegration theory examines whether individually non-stationary series share a common stochastic trend, implying a long-run equilibrium. Despite short-term deviations, Chinese and U.S. equities may be bound together by underlying forces such as global growth, world interest-rate cycles, or bilateral trade intensity.

An Error-Correction Model (ECM) captures the adjustment process: when one market diverges, arbitrageurs and long-horizon investors trade to restore equilibrium, transmitting transient shocks across borders. Recognizing such cointegration allows investors to design hedging or pairs-trading strategies and to assess long-horizon systemic risk.

3.3 Research Hypothesis

H1:The Chinese (CSI 300) and U.S. (DJIA) equity markets are cointegrated; that is, they exhibit a stable long-run equilibrium relationship despite short-run deviations.

4. Index Selection and Data Description

4.1 CSI 300 Index

The CSI 300 is one of the most widely followed benchmarks of China's A-share market. It comprises the 300 largest and most liquid stocks listed on both the Shanghai and Shenzhen exchanges, spanning every major sector. Because of its breadth and depth, the index is an accurate barometer of overall Chinese equity performance and investor sentiment. Its constituents trade actively, data are readily available, and its movements are closely monitored by domestic and international investors alike. Selecting the CSI 300 therefore allows us to capture how Chinese market participants react to—and potentially influence—U.S. market developments.

4.2 Dow Jones Industrial Average (DJIA)

The DJIA is the most recognizable U.S. equity benchmark, consisting of 30 blue-chip companies that are leaders in their respective industries. The index is highly liquid, has a continuous price history reaching back to 1896, and is referenced by investors around the globe. Fluctuations in the Dow are routinely interpreted as signals of U.S. macroeconomic health and frequently spill over into other markets. Consequently, the DJIA serves as an ideal proxy for gauging how global investors perceive—and are affected by—developments in China.

4.3 Data Construction

Daily closing prices for the CSI 300 and the DJIA are collected from 1 March 2017 to 29 December 2023. Trading calendars differ between China (9:30 a.m.–3:00 p.m. Beijing time) and the United States (9:30 a.m.–4:00 p.m. Eastern time) and, because holidays do not fully coincide, the raw series contain non-overlapping days. After deleting all unmatched observations, the final balanced panel comprises 1,613 synchronous daily observations. The cleaned dataset is subjected to unit-root tests, cointegration analysis, vector autoregression (VAR) and impulse-response analysis to assess the nature and strength of China–U.S. equity-market interdependence.

5. Empirical Analysis

5.1 Stationarity Tests

Because the raw time-series data are generally non-stationary, we first test for unit roots using the Augmented Dickey-Fuller (ADF) test. The results are presented in Table 1.

Table 1. ADF Test Results

Indicator	t-stat	1 % crit.	5 % crit.	10 % crit.	p-value	Conclusion
LNSH	-2.472	-3.430	-2.860	-2.570	0.1225	Non-stationary
DLNSH	-29.287	-3.430	-2.860	-2.570	0.0000	Stationary

LNDJIA	-1.507	-3.430	-2.860	-2.570	0.5299	Non-stationary
DLNDJIA	-33.441	-3.430	-2.860	-2.570	0.0000	Stationary

Based on the ADF test results, the ADF statistic for LNSH is smaller in absolute value than the 10 % critical value, so we fail to reject the unit-root null and conclude that LNSH is non-stationary. After first-differencing, the ADF statistic for DLNSH is smaller than the 1 % critical value, indicating that the differenced series is stationary. Similarly, LNDJIA is non-stationary at the 10 % level, whereas its first difference, DLNDJIA, is stationary at the 1 % level. Therefore, both LNSH and LNDJIA are integrated of order one, I(1), and their first-differenced series are stationary, confirming that the volatility of the CSI 300 and the Dow Jones indices is mean-reverting.

5.2 Cointegration Test

Because the first-differenced series are both stationary, we proceed with the Johansen cointegration test. Before running the test, we must determine the optimal lag length for the underlying VAR. Setting the maximum lag to 3, we evaluate six information criteria—LL, LR, FPE, AIC, HQIC and SBIC—reported in Table 2.

Table 2. Lag-Order Selection Criteria for the VAR Model

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	9628.21				2.2e-08	-11.9655	-11.963	-11.9588
1	9674.06	91.713	4	0.000	2.1e-08	-12.0175	-12.01	-11.9974*
2	9684.37	20.617*	4	0.000	2.1e-08*	-12.0253*	-12.0129*	-11.9919
3	9686.71	4.6779	4	0.322	2.1e-08	-12.0233	-12.0059	-11.9764

Asterisks (*) indicate the selected lag under each criterion. The majority of the criteria point to two lags; hence, we specify a VAR(2) as the basis for the subsequent Johansen cointegration analysis.The trace test and the maximum-eigenvalue test both reject the null hypothesis of no cointegration ($r = 0$) at the 5 % critical level. At the same time, both statistics accept the null of at most one cointegrating vector ($r \leq 1$). Therefore, the Johansen test indicates that there is exactly one cointegrating relationship between the two variables, confirming the existence of a long-run equilibrium linkage between the CSI 300 and the Dow Jones Industrial Average.

Table 3. Johansen Cointegration Test

Maximum rank	Params	LL	Eigenvalue	Trace statistic	Critical value 5%
0	10	9243.4092	.	886.6012	15.41
1	13	9487.2742	0.26149	398.8713	3.76
2	14	9686.7098	0.21956		

5.3 VAR Model Estimation

Guided by the lag-length selection in Table 3, we specify a VAR(2) to capture the dynamic interactions between the Chinese and U.S. equity markets. Using the first-differenced, stationary series DLNSH (CSI 300) and DLNDJIA (Dow Jones), the estimated VAR(2) system is

$$\begin{aligned} DLNDJIA &= -0.1472465DLNDJIA(-1) - 0.0048954DLNSH(-1) \\ &+0.1075174DLNDJIA(-2) + 0.0125133DLNSH(-2) + 0.0003783 \end{aligned} \tag{1}$$

$$\begin{aligned} DLNSH &= 0.1429422\,DLNDJIA(-1) - 0.0322433\,DLNSH(-1) \\ &+0.0498919DLNDJIA(-2) - 0.0014785DLNSH(-2) - 0.0000695 \end{aligned} \tag{2}$$

The estimated VAR(2) coefficients reveal clear lagged feedback between the two markets.CSI 300 shocks propagate to the Dow with a delay,a one-day lagged CSI 300 innovation exerts a negative impact on next-day Dow volatility, whereas the two-day lag delivers a positive effect. Dow shocks are likewise transmitted to the CSI 300 with a lag, the first lag of Dow volatility has a negative influence on the Dow itself, while the second lag turns positive.Own-market dynamics,lagged CSI 300 volatility dampens subsequent CSI 300 moves (negative own-effect), whereas lagged Dow volatility boosts subsequent CSI 300 fluctuations (positive cross-effect).

5.4 Stability Diagnostics

For a VAR model to be considered stable, the inverse modulus of every estimated root must be less than 1—i.e., all roots must lie inside the unit circle. If any root falls on or outside the circle, subsequent inferences such as impulse-response functions and variance decompositions become unreliable.

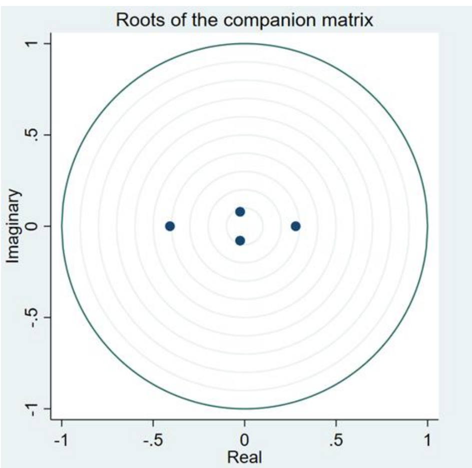

Figure 1 Stability Diagnostics of the VAR Model

As shown in Figure 1, the inverse AR roots of the estimated bivariate VAR(2) all reside strictly within the unit circle. Therefore, the model is dynamically stable and its dynamic simulations are valid.

5.5 Granger-Causality Tests

The Granger-causality test assesses whether movements in one endogenous variable can be treated as exogenous with respect to another. Table 4 reports the results.

Table 4. Granger-Causality Test Results

Equation	Excluded	chi2	df	Prob > chi2
D_lnDJIA	D.lnSH	.27823	2	0.870
D_lnDJIA	ALL	.27823	2	0.870
D_lnSH	D.lnDJIA	34.401	2	0.000
D_lnSH	ALL	34.401	2	0.000

At the 1 % significance level, fluctuations in DLNSH (CSI 300) Granger-cause fluctuations in DLNDJIA (DJIA), whereas the reverse is not true. Consequently, Equation (1)—the specification in which DLNDJIA responds to lagged DLNSH—offers the more statistically valid representation within the estimated VAR framework.

5.6 Impulse-Response Function Analysis

Impulse-response functions (IRFs) are used to trace how a one-standard-deviation shock to one endogenous variable propagates through the system and affects the other variables over time. The IRF results for the CSI 300 (DLNSH) and the Dow Jones Industrial Average (DLNDJIA) are illustrated in Figure 2.

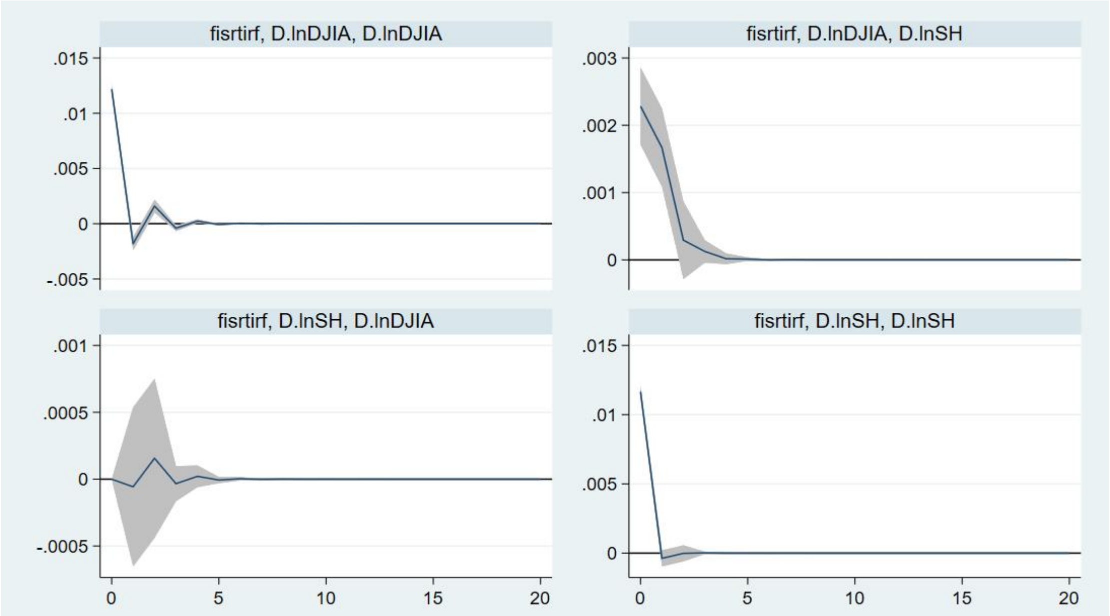

Figure 2. Impulse-Response Functions (IRFs)

5.6.1 A one-unit Positive Shock to DLNDJIA (Dow Jones Volatility)

Self-impact: The Dow Jones immediately experiences its largest positive response in period 0. The effect then declines rapidly, turns negative by period 3, and gradually oscillates around zero, converging to zero by approximately period 6. Overall, the Dow's own shock exerts a positive net effect on itself.

Cross-impact: In the same scenario, the CSI 300 registers its strongest positive reaction on impact (period 0). The effect subsequently diminishes in an oscillatory fashion and becomes negligible by period 5. Thus, a Dow Jones shock has a positive influence on the CSI 300.

5.6.2 A one-unit Positive Shock to DLNSH (CSI 300 Volatility)

Self-impact: The CSI 300 initially jumps to its highest level, then drops sharply, reaches a negative trough in period 2, and gradually returns to zero by period 3. Overall, the CSI 300's own shock has a positive net effect on itself.

Cross-impact: The Dow Jones responds with a slow initial decline, then rises until period 3 when the effect peaks, after which it declines in a damped oscillation and approaches zero by period 5. Consequently, a CSI 300 shock also exerts a positive net influence on the Dow Jones.

In short, both markets display a positive, yet short-lived, response to innovations originating in the other market, with the effects essentially dissipating within five to six trading days.

6. Conclusions and Recommendations

6.1 Conclusions

Empirical evidence confirms the presence of pronounced lagged effects: volatility in the CSI 300 continues to influence subsequent movements in the Dow Jones, and Dow Jones volatility likewise reverberates through the CSI 300 with a similar delay. Each index reacts positively to its own shocks, exhibiting an initial upward surge that gradually subsides and converges to a steady state. A clear bidirectional linkage is also documented: movements in the Dow Jones exert a positive influence on the CSI 300, while shocks originating in the CSI 300 are transmitted positively to the Dow Jones, underscoring a genuine two-way interdependence between the two markets. When a one-unit positive shock is applied to the Dow Jones, its own volatility first spikes upward, then diminishes, reaches a negative trough around the third period, and finally stabilizes; the same pattern is observed when a one-unit positive shock is delivered to the CSI 300, affecting both the index itself and the Dow Jones in a similar oscillatory fashion.

6.2 Recommendations

When formulating investment decisions and risk-management protocols, practitioners should explicitly incorporate these lagged effects; historical volatility patterns should be viewed as forward-looking signals rather than mere background noise. Close attention to the Dow Jones is warranted, as its fluctuations carry valuable predictive content for the CSI 300; conversely, developments in the CSI 300 should be monitored by U.S. investors, because shocks in the Chinese market are transmitted positively to American equities. Given the documented two-way linkage, portfolio and hedging strategies must jointly consider feedback from both markets instead of treating either side as exogenous. Episodes such as the 2008 global financial crisis, the 2015 Chinese stock-market crash, the 2018–2019 U.S.–China trade dispute, and the 2020 COVID-19 pandemic demonstrate that tail risks can be rapidly propagated across the Pacific; stress tests and scenario analyses should therefore explicitly model simultaneous shocks to both markets in order to mitigate cross-border risk and uncover potential opportunities. Finally, the China–U.S. equity nexus should be interpreted within a broader context that also encompasses macroeconomic indicators, political developments, and corporate fundamentals; only by integrating these additional layers of information can investors arrive at more accurate and comprehensive decisions.

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