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Volatility Spillover Benefits of the Hang Seng Index and Shanghai Composite Index: A Vector Autoregressive (VAR) Model and Granger Causality Test Analysis

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Abstract: This study aims to explore the volatility spillover benefits between two major stock markets in Hong Kong and Shanghai, namely the Hang Seng Index and the Shanghai Composite Index. Empirical analysis is conducted using a Vector Autoregressive (VAR) model and Granger causality test based on daily return data from 2013 to 2023. The research finds a significant volatility interaction between the Hang Seng Index and the Shanghai Composite Index, which is more pronounced during periods of global economic instability. Impulse response analysis reveals that positive shocks in Hang Seng Index lead to increased volatility in the short term for the Shanghai Composite Index but gradually weaken to a weak negative effect in the long term. Conversely, positive shocks in the Shanghai Composite Index have a short-term inhibitory effect on the Hang Seng Index but transform into a weak promoting effect in the long term. These findings have important implications for investors and policymakers in risk management, forecasting future stock market trends, and capital allocation.

Keywords: Shanghai Composite Index, Hang Seng Index, volatility, Vector Autoregressive model, Granger causality test

1. Introduction

As the economies of various countries continue to grow rapidly, the stock market has become an essential channel for capital flows and resource allocation. The performance of the Shanghai Composite Index and the Hang Seng Index, as two major stock trading markets in Asia, directly impacts investor confidence and market stability. However, the volatility of these two markets has also attracted widespread attention, particularly in the context of increasing global economic uncertainty. Accurately measuring and explaining the volatility relationship between these two markets has become an important research topic.

This study aims to address three aspects of the volatility characteristics of the Shanghai Composite and Hang Seng Indices: (1) the presence of volatility spillover effects, (2) the time series characteristics of these spillover effects, and (3) the impact of these effects. We begin by reviewing the relevant literature to establish the current state of research and theoretical foundations in this field. Subsequently, we provide a detailed description of the research methods and data processing

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procedures, using a sample of 2191 daily observations from December 31, 2013, to April 11, 2023, for the Shanghai Composite Index and Hang Seng Index. The empirical analysis section presents the results of the model and offers explanations for the volatility spillover benefits. Finally, the paper summarizes the main findings and provides recommendations for future research and practical applications, employing the Vector Autoregressive (VAR) model and Granger causality test to analyze the volatility spillover benefits between the Shanghai Composite Index and the Hang Seng Index. This analysis not only enhances our understanding of the correlation between the two markets but also provides valuable information for policymakers and investors to better manage market risks.

2. Literature Review

Against the backdrop of global financial integration, stock market volatility has become a core issue in the field of finance, with the volatility of different stock markets being a major focus of study for scholars worldwide. The ARCH model proposed by Engle [1] and the GARCH model developed by Bollerslev [2] provided the methodological foundation for quantifying the volatility of individual markets. Diebold and Yilmaz [4] further explored the interplay of volatility among multiple financial markets.

Studies on volatility spillover have primarily focused on quantifying how the volatility of one financial market affects others. Forbes and Rigobon [3] extensively examined this issue in their seminal research. However, most studies have concentrated on markets in developed countries, such as the studies by King et al. [5] and Longin & Solnik [6], with relatively limited research on emerging markets like China, particularly the Shanghai and Hang Seng stock markets, as pointed out by Chan et al. [7].

VAR models and Granger causality tests have found wide application in the study of financial market volatility. Sims [8] emphasized that VAR models capture dynamic relationships among multiple time series, while Hamilton [9] provided statistical foundations for Granger causality testing. Granger [10] applied econometrics to calculate causal relationships.

Currently, research on volatility spillover between the Shanghai and Hang Seng stock markets in China remains a relatively underexplored area. Given the significance of these two markets within the Chinese and global financial systems, understanding their inherent volatility correlation holds substantial practical importance.

3. Empirical Analysis and Conclusion

3.1. Research Methods and Data

This study employs daily return data for the Shanghai Composite Index and Hang Seng Index from December 31, 2013, to April 11, 2023. Data sources include Guotai An, Investing, Bloomberg, and other databases. Data verification and processing are performed using the Augmented Dickey-Fuller (ADF) test. The main research methods include the Vector Autoregressive (VAR) model and Granger causality test for modeling.

3.2. Stationarity Test

Table 1: presents the results of the stationarity test.

Sequence	ADF	1% Critical Value	5% Critical Value	10% Critical Value	Prob.*	Conclusion
HSL	-46.75442	-2.566016	-1.940968	-1.616602	0.0001	Stationary
SH	-44.88716	-2.566016	-1.940968	-1.616602	0.0001	Stationary

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In this study, the Augmented Dickey-Fuller (ADF) unit root test was conducted on the logarithmically transformed data of the two variables using EViews 12.0 software. The results are presented in Table 2. It can be concluded that both HSL and SH are stationary time series. As these two time series exhibit the same order of integration, the prerequisite for establishing a Vector Autoregressive (VAR) model is satisfied.

3.3. Optimal Lag Order Selection

Table 2: VAR Lag Order Selection Criteria

Included observations: 2188

Lag	LogL	LR	FPE	AIC	SC	HQ
0	13168.60	NA	2.03e-08	-12.03528	-12.03008*	-12.03338
1	13179.04	20.85970	2.02e-08	-12.04117	-12.02557	-12.03547
2	13188.41	18.70304	2.01e-08	-12.04608	-12.02007	-12.03658*
3	13189.21	1.580425	2.02e-08	-12.04315	-12.00674	-12.02984
4	13195.80	13.12858	2.01e-08	-12.04552	-11.99870	-12.02841
5	13202.34	13.02112*	2.01e-08*	-12.04784*	-11.99063	-12.02693
6	13206.03	7.329340	2.01e-08	-12.04756	-11.97994	-12.02284

From the above table, it can be deduced that the optimal lag order for the VAR model is 5. (The table presents five criteria values for the model, namely Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Information Criterion (HQIC). The lag order corresponding to the most asterisks (*) is selected as the optimal lag order.)

3.4. Cointegration Test

Table 3: Trend assumption: Linear deterministic trend

Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.174350	787.3769	15.49471	0.0000

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Table 3: (continued).

At most 1 *	0.154464	367.6159	3.841465	0.0000

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.174350	419.7611	14.26460	0.0000
At most 1 *	0.154464	367.6159	3.841465	0.0000

Preliminary cointegration analysis: The trace test and maximum eigenvalue test reject the null hypothesis at a 95% confidence level (indicating rejection of the hypothesis that there is no cointegration relationship), suggesting that there are at least 2 cointegrating equations between these two variables. In conclusion, there exists a long-term cointegration relationship between these two variables.

3.5. Establishment of the VAR Model

Table 4: Vector Autoregression Estimates
Standard errors in ( ) & t-statistics in [ ]

	HSL	SH			
HSL(-1)	0.036815 (0.02562) [1.43689]	0.016741 (0.02646) [0.63264]	SH(-1)	-0.063132 (0.02478) [-2.54739]	0.035211 (0.02560) [1.37569]
HSL(-2)	0.013065 (0.02557) [0.51097]	0.090737 (0.02641) [3.43607]	SH(-2)	-0.040390 (0.02485) [-1.62557]	-0.090426 (0.02566) [-3.52384]
HSL(-3)	-0.010510 (0.02564) [-0.40989]	0.003118 (0.02648) [0.11774]	SH(-3)	0.005501 (0.02491) [0.22077]	0.017050 (0.02573) [0.66259]
HSL(-4)	0.082804 (0.02563) [3.23129]	0.016781 (0.02647) [0.63408]	SH(-4)	-0.040172 (0.02483) [-1.61804]	0.023426 (0.02564) [0.91362]
HSL(-5)	-0.016136	-0.021591	SH(-5)	0.030442	-0.035871

Table 4: (continued).

	(0.02559)	(0.02643)		(0.02478)	(0.02559)
	[-0.63049]	[-0.81685]		[1.22866]	[-1.40181]
C	-2.95E-06	0.000312			
	(0.00027)	(0.00028)			
	[-0.01079]	[1.10397]			

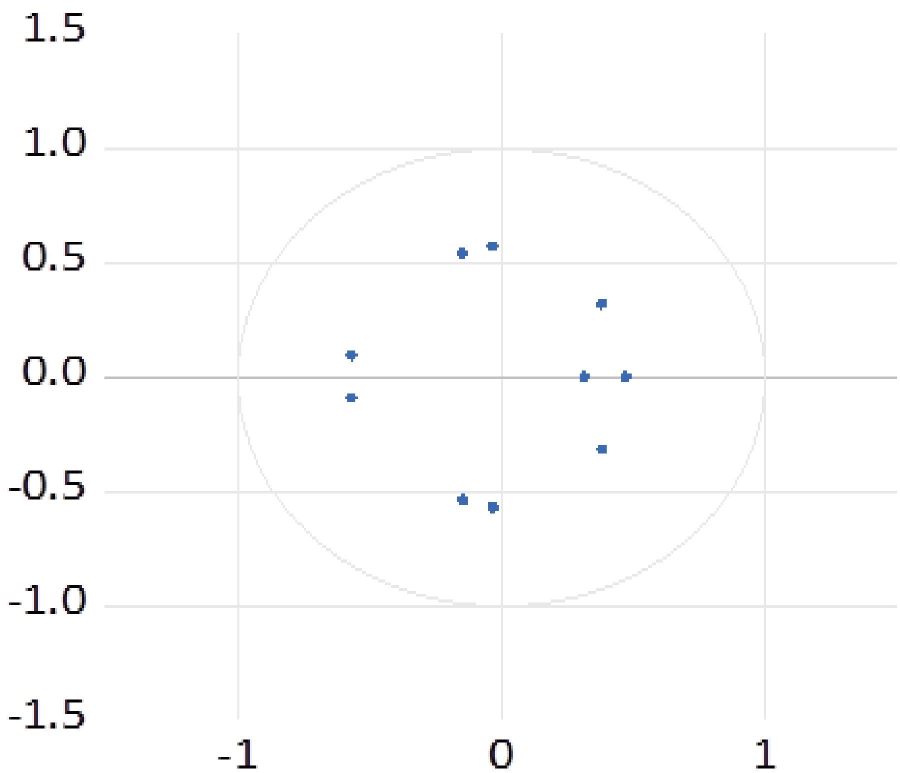

Figure 1: Inverse Roots of AR Characteristic Polynomial

3.6. Verification of Model Stability through AR Root Testing

The stability of a model can be assessed by examining the reciprocals of the absolute values of the roots of the AR characteristic equation. If these roots are within the unit circle, the model is considered stable. Otherwise, the model is unstable, and certain results (such as the standard errors of impulse response functions) are not valid. After establishing the cointegration relationship between variables, the stability of the model is verified by examining the AR roots. In this model, all 10 AR unit roots are within the unit circle, indicating stability.

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3.7. Granger Causality Test

Table 5: Pairwise Granger Causality Tests
Lags: 5

Null Hypothesis:	Obs	F-Statistic	Prob.
SH does not Granger Cause HSL	2191	2.61848	0.0228
HSL does not Granger Cause SH		2.65251	0.0213

Under the optimal lag order of 5, the Granger causality test is conducted. At a 5% significance level, the rejection of the hypothesis that "SH volatility does not Granger-cause HSL" implies a significant Granger influence of SH on HSL, indicating that SH returns have a spillover effect on HSL returns.

Similarly, at a 5% significance level, the rejection of the hypothesis that "HSL volatility does not Granger-cause SH" implies a significant Granger influence of HSL on SH, indicating that HSL returns also have a spillover effect on SH returns.

3.8. Impulse Response Analysis

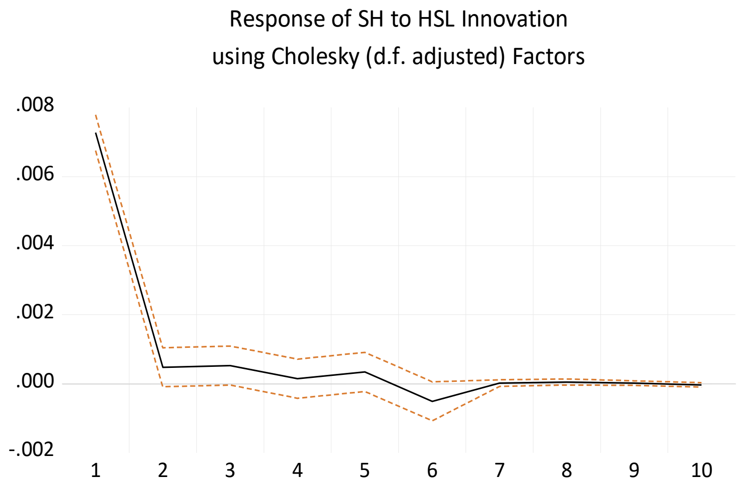

Figure 2: Examination of the impulse response graph

HSL's effect on SH reveals that an increase in HSL in the current period, representing a shock, has an overall positive effect on future SH returns, showing a promoting effect. Specifically, the positive effect sharply decreases in the 1st to 2nd periods, continues to decline from the 2nd to the 5th period, turns negative in the 6th period, and gradually decreases until it approaches zero. In summary, HSL's growth initially promotes SH growth but weakly inhibits it in the later stages.

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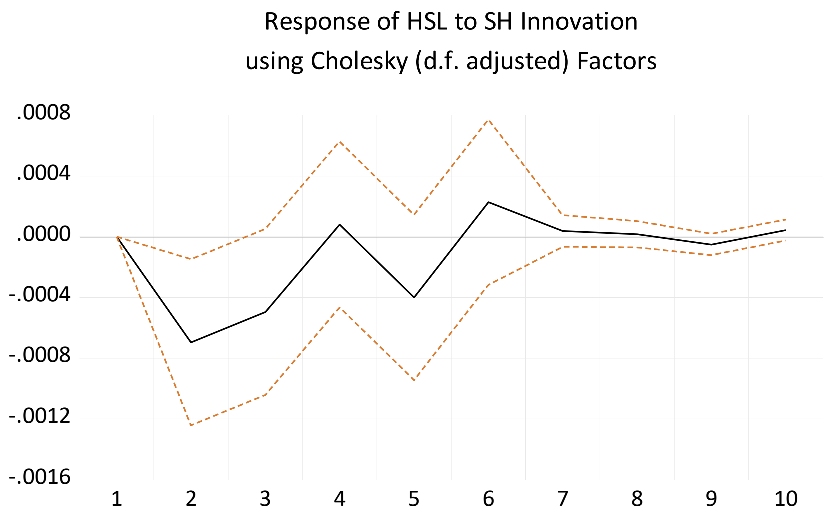

Figure 3: Impulse response results for SH regarding HSL

Similarly, examination of the impulse response graph for SH's effect on HSL reveals that an increase in SH in the current period, representing a shock, has an overall negative effect on future HSL returns in the earlier periods and a weak positive effect in the later periods. Specifically, the negative effect increases initially from the 1st to 4th periods, followed by a decrease from the 4th to the 6th period. Starting from the 6th period, a positive effect emerges, gradually decreasing until it approaches zero. In summary, SH's growth initially inhibits HSL's growth but weakly promotes it in the later stages.

3.9. Modeling with GARCH

While the Granger test confirms the existence of spillover effects between HSL and SH returns, GARCH (1,1) models are separately applied to HSL and SH to capture the conditional variance aspects, i.e., volatility.

Table 6: Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
I Dependent Variable: HSL
Convergence achieved after 25 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000273	0.000232	1.177730	0.2389
	Variance Equation			
C	2.76E-06	5.48E-07	5.044802	0.0000

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Table 6: (continued).

RESID(-1)^2	0.066845	0.006603	10.12338	0.0000
GARCH(-1)	0.916617	0.007936	115.5000	0.0000
Dependent Variable: SH				
Convergence achieved after 23 iterations				
C	0.000318	0.000202	1.570199	0.1164
	Variance Equation			
C	1.31E-06	2.53E-07	5.170664	0.0000
RESID(-1)^2	0.086915	0.004864	17.86885	0.0000
GARCH(-1)	0.909852	0.004407	206.4608	0.0000

3.10. Granger Test for GARCH (HSL) and GARCH (SH)

Table 7: Pairwise Granger Causality Tests

Null Hypothesis:	Obs	F-Statistic	Prob.
Lags: 1			
GARCHSH does not Granger Cause GARCHHSL	2195	3.44471	0.0636
GARCHHSL does not Granger Cause GARCHSH		4.35024	0.0371
Lags: 2			
GARCHSH does not Granger Cause GARCHHSL	2194	1.52758	0.2173
GARCHHSL does not Granger Cause GARCHSH		4.96905	0.0070

Granger tests are conducted for lag periods 1, 2, 3, and 4. It is observed that only in the 1st lag period, at a 10% significance level, the hypothesis that "GARCHSH volatility is not a Granger cause of GARCHHSL" is rejected, indicating that GARCHSH has a significant Granger influence on GARCHHSL, and thus, GARCHSH exhibits a spillover effect on GARCHHSL. In contrast, GARCHHSL's spillover effect on GARCHSH occurs in the 1st to 4th lag periods.

4. Research Conclusion and Findings

The research results concerning the Shanghai Composite Index (SH) and the Hang Seng Index (HSL) support a significant bidirectional Granger causality relationship at a 5% significance level, indicating that the volatility between SH and HSL exhibits mutual influence characteristics.

After adjusting for the GARCH model, Granger causality tests with a lag order of 1 further confirm that SH has a significant Granger influence on HSL. Additionally, for lag orders ranging from 1 to 4, HSL also demonstrates a significant Granger influence on SH. This finding reveals the dynamic nature of volatility interaction between the two markets over different time spans.

Impulse response analysis further reveals the dynamic characteristics of this volatility interaction. Specifically, a positive shock in HSL promotes SH volatility in the short term, but this effect gradually weakens and eventually turns into a weak negative effect in the long term. Conversely, a positive shock in SH initially inhibits HSL in the short term but gradually transitions into a weak promoting effect in the long term.

This series of complex and nuanced interactions provides new insights for risk management and capital allocation. It holds significant academic and practical value for understanding the underlying interconnection mechanisms of China's two major stock markets.

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