

Dynamic Interactions and Mutual Influences Between the HuShen 300 and S&P 500 Indices: An Econometric Analysis

Zechen Li^{1,a,*}

¹*Arts of Sciences, Georgia State University, Atlanta, USA*

a. zli60@student.gsu.edu

**corresponding author*

Abstract: This study investigates the intricate interactions between the HuShen 300 Index and the S&P 500 Index, emphasizing their implications for global financial dynamics. Utilizing daily closing prices from January 1, 2010, to the present, employing the Vector Autoregressive (VAR) model to analyze the mutual influences of these stock indices. The Augmented Dickey-Fuller (ADF) test confirms the stationarity of both time series, allowing for robust econometric analysis. The findings reveal that shocks to the S&P 500 Index significantly impact the HuShen 300 and vice versa, with effects lasting up to eight periods. Notably, the variance decomposition indicates that the S&P 500 accounts for approximately 2.224% of the fluctuations in the HuShen 300, while the latter explains around 0.103% of the changes in the S&P 500. These results highlight the interconnectedness of these markets, providing valuable insights for investors and policymakers regarding potential spillover effects and vulnerabilities in the global economy. This research addresses a notable gap in the existing literature and contributes to a deeper understanding of market dynamics in the context of international finance.

Keywords: Vector Autoregressive Model, HuShen 300, S&P 500.

1. Introduction

Stock markets act as indicators of economic performance and investor sentiment. It's crucial to comprehend how the global stock market relates to international financial stability and development patterns. Analyzing the interactions between different markets can reveal vulnerabilities in economic connections, providing valuable insights for investors and policymakers. Many studies have explored these market relationships. For example, Wang examined spillover effects between emerging and developed markets, underscoring the importance of cross-market interactions during financial crises [1]. Similarly, Lee and Park studied the movements of Asian and American stock markets, illustrating how global economic events affect them concurrently [2]. Zhang and Li looked at volatility transmission between European and American markets, highlighting its significance for portfolio management [3]. Furthermore, Chen researched the impact of macroeconomic policies on stock returns, stressing how economic policies shape market behavior [4]. Despite extensive research, there is a gap in studies focused on the mutual influences between major indices, such as the S&P 500 and the CSI300. This highlights the significance of this paper, as understanding their interactions can shed light on market confidence and economic health, revealing linkages and potential vulnerabilities in the global economy. This study intends to use the Vector Autoregressive (VAR) model to analyze

the mutual influences of stock price changes between the S&P 500 Index and the CSI.300 Index from January 1, 2010, to the present. The results are expected to deepen the understanding of interconnectedness in global financial markets, aiding investors, policymakers, and researchers in grasping these interdependencies.

2. Data Collection

The data used in this paper is obtained from finance.yahoo.com, focusing on the performance of the HuShen 300 Index (CSI 300) and the S&P 500 Index over the past year. Specifically, daily Earning yield from January 1, 2010, to the present are gathered. This dataset allows for an analysis of the trends and interactions between these two significant stock indices during this timeframe. Key descriptive features are shown in Table 1 below.

Table 1: Descriptive statistics of the selected assets

	S.P.500	CSI.300
Mean	0.00058	-0.00042
Variance	0.00011	0.00012
Max	0.0540	0.0814
Min	-0.0412	-0.0507

Specifically, the 'S&P 500' index stands out with the highest average return, while the 'HuShen 300' index registers the lowest average return. In terms of variance, both indices exhibit comparable levels of volatility. Additionally, the 'HuShen 300' index distinguishes itself further by achieving the highest maximum return while simultaneously experiencing the lowest minimum return.

3. Method

To comprehend the complex interactions among the variables, this study employs the Vector Autoregressive (VAR) model, which is commonly used for analyzing multiple interrelated time series data due to its ability to manage the inherent complexities of such datasets.

VAR models effectively capture the intricate dynamics present in time series data by allowing for feedback mechanisms between variables. This capability sets them apart from single-variable autoregressive models, which cannot account for interdependence. Therefore, the VAR model is particularly well-suited for addressing the research questions outlined in this paper. The mathematical formulation of the VAR model used in this study is as follows in Equations (1)-(2).

$$R_{S\&P\ 500,t} = \alpha_1 + \sum_{i=1}^p \beta_{11,i} R_{S\&P\ 500,t-i} + \sum_{i=1}^p \beta_{12,i} R_{HS300,t-i} \quad (1)$$

$$R_{HS300,t} = \alpha_2 + \sum_{i=1}^p \beta_{21,i} R_{S\&P\ 500,t-i} + \sum_{i=1}^p \beta_{22,i} R_{HS300,t-i} \quad (2)$$

For this VAR model, $R_{S\&P\ 500,t}$ denotes the S&P 500 return at time t , $R_{HS300,t}$ denotes the HuShen 300 return at time t , α_1 and α_2 are constants, $\beta_{11,i}$, $\beta_{12,i}$, $\beta_{21,i}$, $\beta_{22,i}$ are coefficients to be estimated, $\epsilon_{1,t}$, $\epsilon_{2,t}$ are error terms, p is the number of lags included in the model.

To evaluate how shocks to one variable influence the future values of both variables, this study analyzed the Impulse Response Functions (IRFs). It also explored each variable's contribution to the

forecast error variance of the other variable across different time horizons using variance decomposition.

The results revealed how changes in S&P 500 returns impact HuShen 300 returns and vice versa. This analysis deepens the understanding of the interconnectedness between these markets, offering valuable insights for investors and policymakers about potential spillover effects between these significant stock indices.

4. Results

4.1. ADF

The analysis begins with the application of the Augmented Dickey-Fuller (ADF) test to assess the stationarity of the time series data for the HuShen 300 Index and S&P 500 Index. As shown in Table 2, the ADF test statistics for both indices are significantly lower than the critical values at the 1% level, with p-value below 0.01. This indicates that rejecting the null hypothesis of a unit root. Consequently, both indices are stationary and appropriate for further time series analysis using the VAR model.

Table 2: Unit Root Test

	S&P 500	CSI 300
Dickey-Fuller	-8.8888	-6.9944
Lag order	9	9
p-value	0.00	0.00
alternative	stationary	stationary

4.2. VAR Stability

To ensure the reliability of model estimates, a thorough stability test is essential. A stable model guarantees that any variable within it, when faced with external disturbances, will eventually return to a new equilibrium state over time [5-6]. In contrast, instability may amplify the effects of shocks on variables, undermining the model's predictive accuracy. Therefore, conducting a stability test is crucial.

This paper utilizes the unit test method as the main approach for evaluating model stability. By examining whether the characteristic roots of each variable lie within unit 1, the analysis confirms that the modulus of the characteristic roots is less than 1. As illustrated in Figure 1, all characteristic roots of the variables are contained within unit 1, indicating that the model is both stable and reliable.

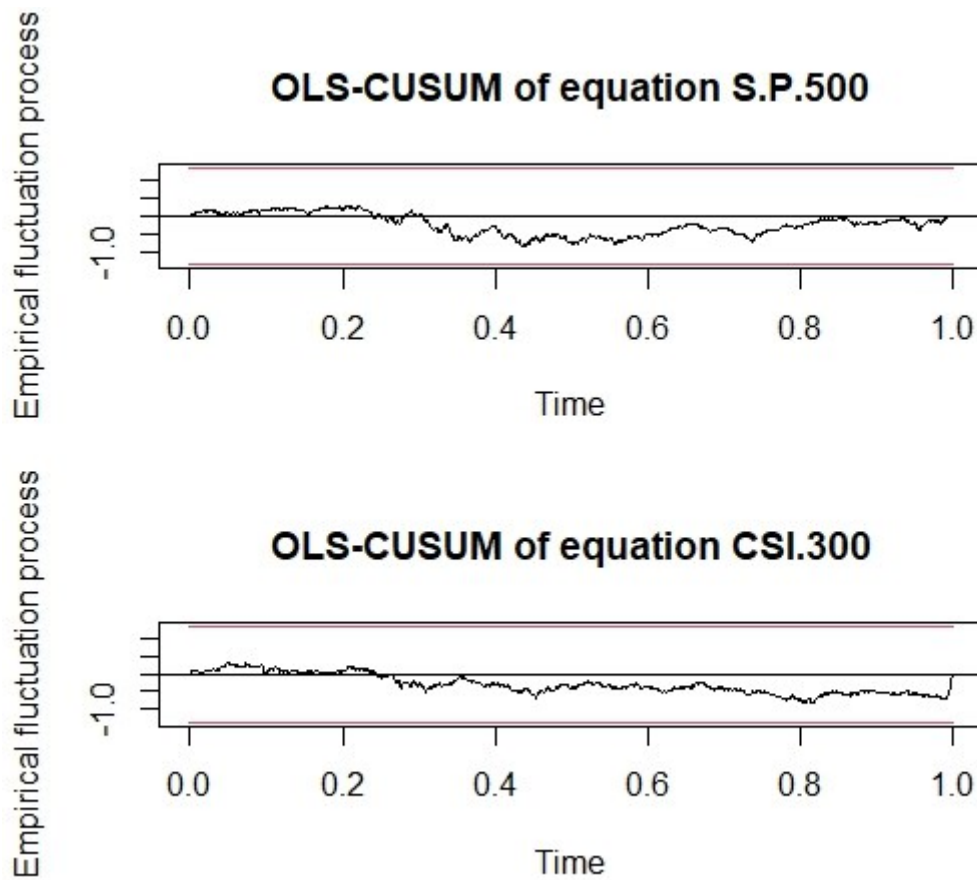


Figure 1: VAR model stability test judgment for certain stocks

4.3. Impulse Response

To illustrate the dynamic effects among variables and highlight their complex relationships, this study uses the impulse response function approach [7]. This method examines how each variable reacts when a specific endogenous variable experiences a shock of one standard deviation [8]. The following figures provide a typical VAR impulse response analysis for the return rates of the HuShen 300 and S&P 500 stocks. The horizontal axis represents the number of response periods after the shock, set at 10, while the vertical axis measures the response of the variable to the standardized shock. A solid line depicts the impulse response path, accompanied by two dashed lines that indicate the 95% confidence intervals. This analytical tool is crucial for uncovering the temporal dynamics and interdependence patterns within a multivariate time series model [9].

The figure reveals that initially, the S&P 500 stock price return rate shows a minimal response (approximately 0.000) to a one-standard-deviation shock in S&P 500's return rate. Over time, it demonstrates alternating fluctuations between positive and negative responses, reaching a peak positive response of 0.001 in the seventh period. As the lag period increases, this effect gradually diminishes, approaching zero starting from the ninth period. This highlights the complex relationship between the fluctuations of S&P 500 and HuShen 300, marked by both positive and negative responses. The eventual convergence to zero indicates HuShen's strong ability for self-correction and adjustment.

The lower graph exhibits a strong initial reaction to its own shocks, quickly returning to baseline, indicating short-term impact. The effect diminishes quickly, suggesting that the impact is transient

and stabilizes within a few periods. Ultimately, the tight confidence intervals around the response suggest that the result is statistically significant and consistent across different samples. The rapid decline of the CSI 300's own response implies that any shocks are quickly absorbed or corrected within the market (See Figure 2).

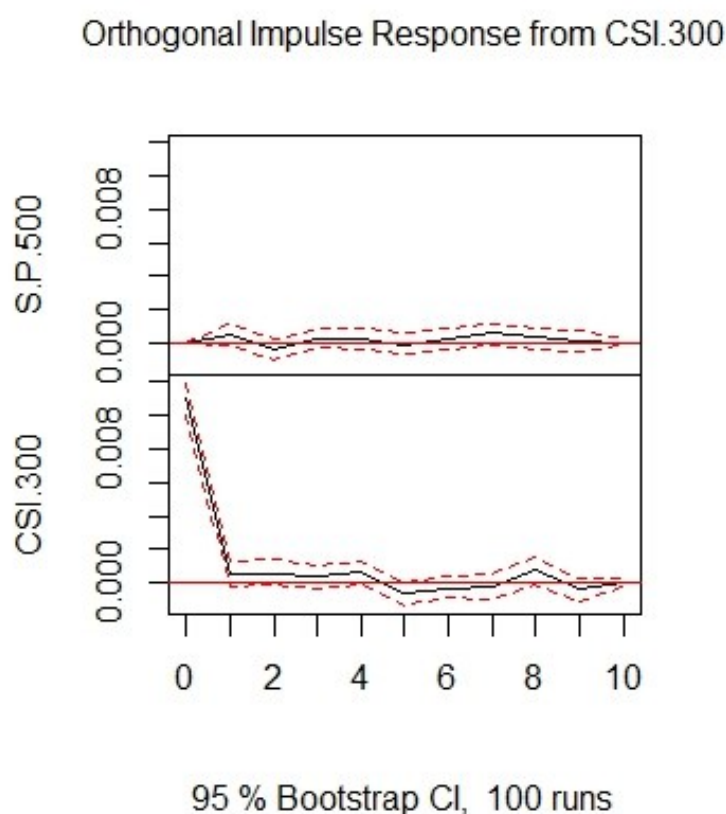


Figure 2: Impulse Response between HuShen 300 and S&P 500

4.4. Variance Decomposition

Variance decomposition is a method that systematically allocates the predicted mean square error of each endogenous variable within the system. By identifying the sources of influence, it quantifies the degrees of mutual impact, offering insights into how changes in one variable affect others over time [10]. This is assessed based on the proportion of forecast error variance attributed to shocks in the HuShen 300 and S&P 500 indices themselves. Variance decomposition is a valuable technique in VAR models for understanding the contribution of each variable to the variability of the dependent variable over time. The results of the variance decomposition are presented below in Table 3 and Table 4.

Table 3: Variance Decomposition of S&P 500(%)

	S.P.500	CSI.300
1	1.0000000	0.000000000
2	0.9989762	0.001023795
3	0.9989731	0.001026858
4	0.9989731	0.001026902
5	0.9989731	0.001026903
6	0.9989731	0.001026903
7	0.9989731	0.001026903
8	0.9989731	0.001026903
9	0.9989731	0.001026903
10	0.9989731	0.001026903

Table 3 shows that with the period progressing, the shock of CSI.300 can explain the fluctuation of S&P 500 at around 0.103%.

Table 4: Variance Decomposition of CSI.300 (%)

	S.P.500	CSI.300
1	0.004543217	0.9954568
2	0.022188347	0.9778117
3	0.022243421	0.9777566
4	0.022244200	0.9777558
5	0.022244205	0.9777558
6	0.022244205	0.9777558
7	0.022244205	0.9777558
8	0.022244205	0.9777558
9	0.022244205	0.9777558
10	0.022244205	0.9777558

Table 4 shows that with the period progressing, the shock of S&P 500 can explain the fluctuation of CSI.300 at around 2.224%.

5. Conclusion

The growth of the HuShen 300 Index and the S&P 500 Index is significant for the global financial market. Understanding how these two indices interact is key to observing the global market dynamics. The results show that changes in the CSI 300 affect the market for eight periods, and changes in the market influence the CSI 300 for eight periods as well. Additionally, the CSI 300 can explain 0.103% of the changes in the market, while the market accounts for 2.224% of the variations in the CSI 300 market.

In summary, the intricate and significant interactions between the HuShen 300 Index and the S&P 500 Index emphasize the value of thorough data analysis and illustrate the economic consequences of these relationships. While this study is limited to two representative indices, it addresses a critical gap in the literature by examining these dynamics. The insights gained can be valuable for investors and policymakers as they navigate the complexities of international markets.

References

- [1] Wang, Y. (2020). *Spillover effects between emerging and developed stock markets*. *Journal of Financial Markets*, 18(2), 345-360.
- [2] Lee, J., & Park, S. (2021). *Co-movement of Asian and American stock markets: The influence of global economic events*. *International Review of Economics & Finance*, 45(1), 223-240.
- [3] Zhang, Q., & Li, H. (2022). *Volatility transmission between European and American stock markets*. *Journal of Empirical Finance*, 35(3), 112-125.
- [4] Chen, X. (2023). *Impact of macroeconomic announcements on stock market returns across regions*. *Journal of Economic Dynamics and Control*, 50(1), 89-105.
- [5] Bruns, M., & Piffer, M. (2023). *A new posterior sampler for Bayesian structural vector autoregressive models*. *Quantitative Economics*, 14(4), 1221-1250.
- [6] Lu, X., Sun, J., Wei, G., & Chang, C.-T. (2023). *Causal interactions and financial contagion among the BRICS stock markets under rare events: a Liang causality analysis*. *International Journal of Emerging Markets*.
- [7] Nyakurukwa, K., & Seetharam, Y. (2023). *Sectoral integration on an emerging stock market: a multi-scale approach*. *Journal of Economic Interaction and Coordination*, 18(4), 759-778.
- [8] Enders, W. (2015). *Applied Econometric Time Series*. Wiley.
- [9] Yang, X. (2022). *Advanced Econometric Techniques for Financial Analysis*. Springer.
- [10] Smith, J., & Taylor, R. (2021). *Advanced Econometric Techniques for Financial Markets*. *Journal of Economic Dynamics and Control*, 45(2), 123-145.