Research of the Relationship Between S&P 500 Index and SSE Index Under Vector Autoregressive Model

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Abstract. With the escalating conflicts between China and the United States, there is an increasing need to research the relationship between the Chinese and U.S. capital markets. In this study, the return of the SSE index is used to represent the Chinese capital market, while the return of the S&P 500 index represents the U.S. capital market. A vector autoregressive model with an optimal lag is constructed, followed by a Granger causality test. The results indicate that the return of the S&P 500 index Granger causes the return of the SSE index. Furthermore, an impulse response function analysis reveals that there might be a mutual effect between the SSE and S&P 500 indices over a five-month period. Additionally, variance decomposition analysis provides insights into the contribution of other variables. Overall, this research sheds light on the interdependencies and dynamics between the Chinese and U.S. capital markets amidst the ongoing geopolitical tensions.

Keywords: China, US, VAR.

1. Introduction

With the influence from globalization, relationship between capital markets in different countries is becoming more linked [1]. Simultaneously, both China and the U.S. are increasingly influential for global economy [2]. And the directions of different markets always show to be opposite [3]. Therefore, it is a significant part in global market to research on the relationship between China capital market and the U.S for analyzing global capital market.

This passage uses S&P 500 Index and Shanghai Stock Exchange Index (SSE) to represent different capital markets in different countries and calculates monthly return of each index between 2009 and 2023. As for the stationarity test, this paper uses Augmented Dickey-Fuller method to check the stationarity. After stationarity test, this paper has constructed VAR model successfully in the optimal lag. With the constructed model, result from autoregressive unit root test has confirmed stability of the model and this model do not have the spurious regression. By Granger causality test, result show that the fluctuation of return of S&P 500 Index might be Granger-cause of the change of return of SSE Index, without opposite relationship and subsequently this paper finds that fluctuation of return of S&P 500 Index might cause the change of SSE Index. And Impulse Response function reflect and quantify the dynamic relationship between them. Both have similar reactions of themselves and others. In addition, variance decomposition helps us to understand the source of the change of return of S&P 500 Index and SSE Index, apart from itself with the influential extent. Result indicates that SSE Index return have only a slight influence on S&P 500 Index return, but S&P 500 Index return have much more influence on that SSE Index return.

Relationship between China and the U.S. capital market, two of the biggest capital markets around the world, is a significant part for researcher to understand. As for investors, correlation of the two of the biggest capital markets play a big role in consideration of allocating asset and capital portfolio.

2. Source of Data, Data Description and Model Description

2.1. Source of Data

This passage uses monthly data of S&P 500 Index (SPX) return and Shanghai Stock Exchange Index (SH) return between 2009 and 2023. Data are from CSMAR (China Stock Market and Accounting Research Database). The Table 1 describes the data.

Table 1. Data Description

Variables	Observations	Mean	Std. Dev.	Min	Max
SPX (%)	180	0.010	0.044	-0.125	0.127
SH (%)	180	0.005	0.062	-0.226	0.206

The Table 1 show the mean, standard deviation, minimum variable, and maximum variable about the 180 observations.

2.2. Model Description

The Vector Autoregressive model is a widely accepted model in finance and econometric area. VAR model can be used to describe data, analyze dynamic interrelation, and measure influence between variables in different time [4]. The VAR model represents equations, where each equation explains the influence of their own lagged values and other lagged values in the past. Mathematically, the equations represent in following Equation (1):

$$Y_t = (A_1 Y_{t-1} + \cdots A_P Y_{t-P}) + (B_1 X_{t-1} + \cdots B_{t-1} X_{t-P}) + \cdots + e_t + c_t \quad (1)$$

In Equation (1), A1, …. AP represent the coefficient matrices of endogenous variables, and Yt, ... Yt-p represent the metric of endogenous variable, and B1 … BP represent coefficient matrices of other variables, and Xt, ... Xt-p represent metrics of other variables, and et represent the error term, and ct represent the intercept for equation. After constructing VAR model, the model can be used to different purposes: examining Granger causality, analyzing impulse response function (IRF), decomposing variance. IRF indicate that when shocking one variable, the response from each variable, which quantify the influence from one variable. And variance decomposition is helpful for measuring the portion of forecast variance error contributed by others and itself [5].

3. Empirical Analysis

This passage uses Stata MP/16.0 to analyze and visualize data.

3.1. Time Series Construction and Stationarity Tests

This passage constructs two time series by S&P 500 and Shanghai Index return from 2009 to 2023. Each series contain 180 data. And use Augmented Dickey-Fuller (ADF) test to test constructed time series stationarity, which is one of the most widely accepted method [6]. ADF test null hypnosis are following:

Null Hypnosis H0: Time Series are not stationarity series.

Alternative Hypothesis H1: Time Series are stationarity series.

This passage uses Stata to test stationarity for two constructed time series, Table 2 describes the data.

Table 2. Results of Stationarity Test

Series	Test Statistic	P- value	Reject H0
SPX	-14.833	0.0000	Yes
SH	-11.937	0.0000	Yes

As show in Table 2, there is not a time series whose p value is greater than 0.05. Thus, they can reject null hypnosis and are stationarity series.

3.2. Model Construction

To construct suitable VAR model, it needs to select optimal lag order. This passage compares different lags with 0,1,2,3 and 4 relevant parameters to select optimal lag order. Table 3 describes the data about different lags.

Table 1. VAR Model Comparison with Different Lags

Lag(s)	FPE (n)	AIC (n)	HQIC (n)	SBIC (n)	LR (n)
0	6.0e-06	-6.351	-6.336*	-6.315*	\
1	6.0e-06	-6.342	-6.298	-6.234	6.353
2	6.0e-06*	-6.352*	-6.279	-6.172	9.755*
3	6.1e-06	-6.334	-6.232	-6.082	4.932
4	6.2e-06	-6.321	-6.189	-5.996	5.607

As show in table, comparing FPE(n), AIC(n), HQIC(n), SBIC(n) and LR(n), the data with * sign is the optimal lag order in different ways. Therefore, the optimal lag order is 2. With the optimal lag, data of constructed VAR model is presented in Table 4.

Table 4. VAR Model Information

		Coef.	Std. Err.	z	P >|z|	95% Conf. Interval	
SH							
SH	L1.	0.133	0.080	1.66	0.096	-0.024	0.289
	L2.	-0.073	0.079	-0.93	0.350	0.227	0.081
SPX	L1.	-0.057	0.112	-0.51	0.612	-0.277	0.163
	L2.	-0.089	0.111	-0.8	0.423	-0.306	0.128
	Cons	0.005	0.005	1.07	0.285	-0.004	0.015
SPX							
SH	L1.	0.063	0.054	1.17	0.241	-0.043	0.170
	L2.	0.104	0.053	1.94	0.052	-0.001	0.208
SPX	L1.	-0.190	0.076	-2.49	0.013	-0.339	-0.040
	L2.	-0.210	0.075	-2.79	0.005	-0.357	-0.062
	Cons	0.015	0.003	4.50	0.000	0.008	0.021

According to the information in Table 4, this passage constructs following models with Equation (2) and (3):

$$SH_t = 0.133SH_{t-1} - 0.073SH_{t-2} - 0.0570SPX_{t-1} - 0.089SPX_{t-2} + 0.005 \quad (2)$$

$$SPX_t = 0.063SH_{t-1} + 0.104SH_{t-2} - 0.190SPX_{t-1} - 0.210SPX_{t-2} + 0.015 \quad (3)$$

3.3. Autoregressive Unit Root Test

AR Unit Root Test can test whether the fitted VAR model satisfies dynamically stability conditions. If all eigenvalues are inside unit circle, the VAR model pass the dynamic stable test and have dynamic stability. The Fig. 1 shows the unit circle and eigenvalues.

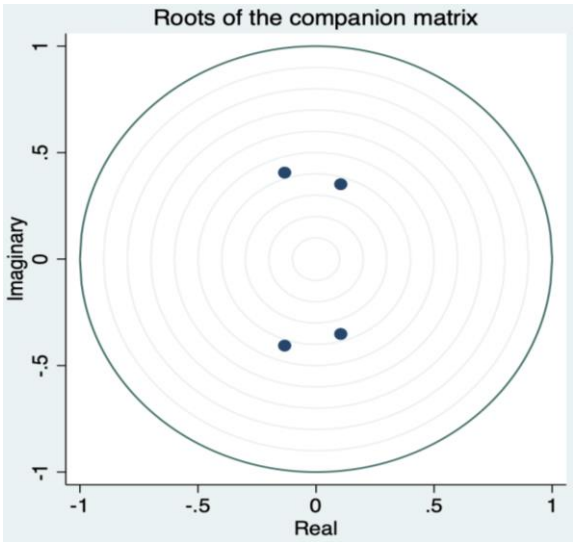


Figure 1. Unit Circle and Eigenvalue

As show in Fig. 1, all the eigenvalues lie inside the unit circle, and constructed VAR model satisfies conditions.

3.4. Granger Causality Test

Granger causality test can test the relationship between SH and SPX. And this paper can have following hypnosis:

Null hypnosis: SH is not Granger-cause of SPX.

Alternative hypnosis: SH is Granger-cause of SPX.

This passage use Stata take the Granger Causality Test and have following data in Table 5:

Table 5. Granger Causality Test Result of SH

Equation	Excluded	P- value	Reject H0
SH	SPX	0.665	No

According to Table 5, P value is greater than 0.10, null hypnosis cannot be rejected. And the SH is not Granger-cause of SPX.

In addition, then this paper can have following hypnosis:

Null hypnosis: SPX is not Granger-cause of SH.

Alternative hypnosis: SPX is Granger-cause of SH.

This paper has following data in Table 6:

Table 6. Granger Causality Test Result of SPX

Equation	Excluded	P- value	Reject H_0
SPX	SH	0.058	Yes

According to Table 6, P value is not greater than 0.10, null hypnosis can be rejected. And the SPX is Granger-cause of SH.

3.5. Impulse Response Function Analysis

Impulse Response Function (IRF) Analysis aims to observe what might would happen and interdependency between variables in following lag times, after adding one positive standard deviation [7]. The follows are IRF analysis for two time series variables.

The finding by observing Fig. 2 is that when the impulse of SH to and SPX, SPX have slight positive in first two months following with decreasing to negative response in the fourth and fifth month.

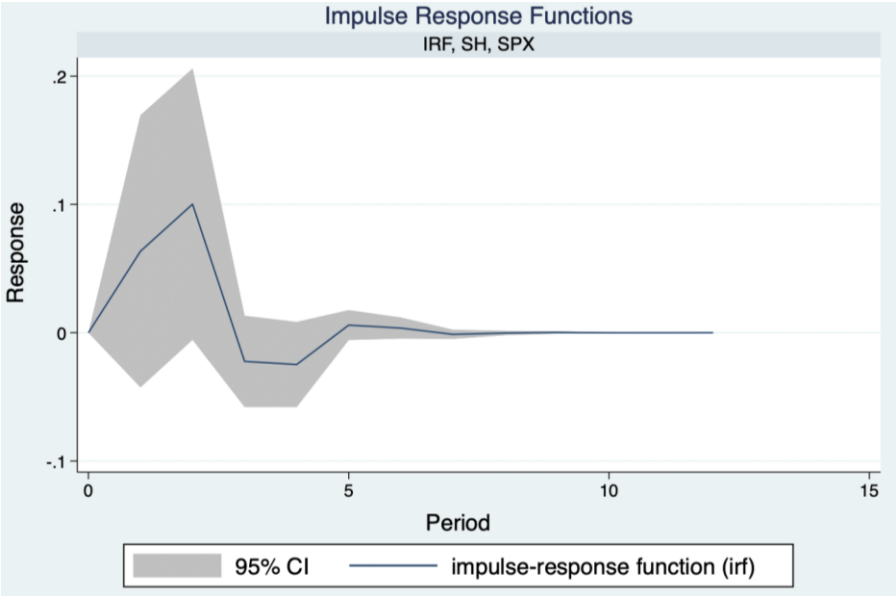


Figure 2. IRF graph of SH

The finding by observing Fig. 3 is that when the impulse of SPX to SH, and SH have slight negative responses in first two months, and subsequently increase to fluctuated nearly zero in the fourth and fifth month.

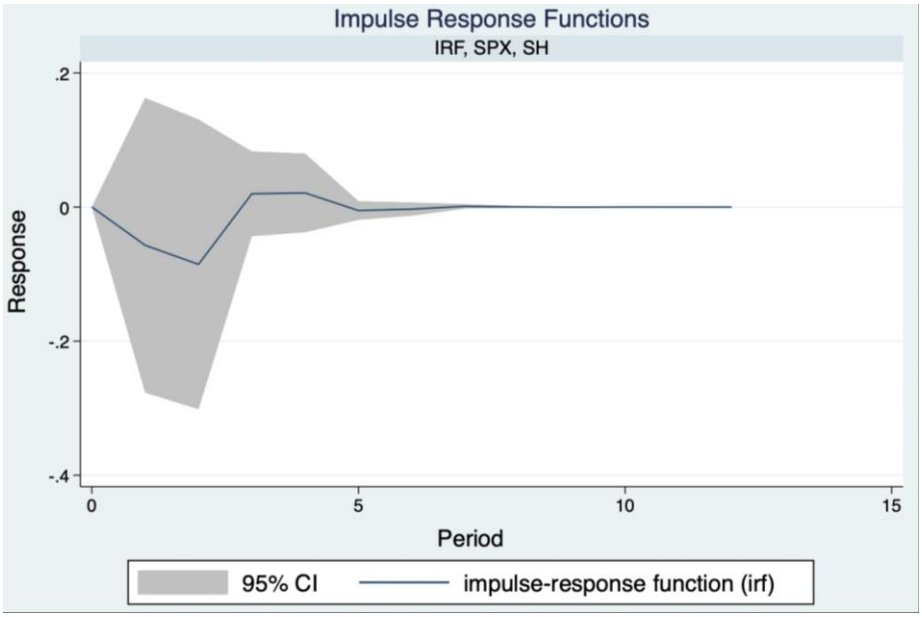


Figure 3. IRF graph of SPX

3.6. Variance Decomposition

The purpose of variance decomposition of VAR model is that variance of the forecast error is divided into influence from proportions of all variables include itself and indicate exogeneity or endogeneity of variables. Apart from itself, Fig. 4 shows the contribution of another variable. SPX contribute nearly 15%.

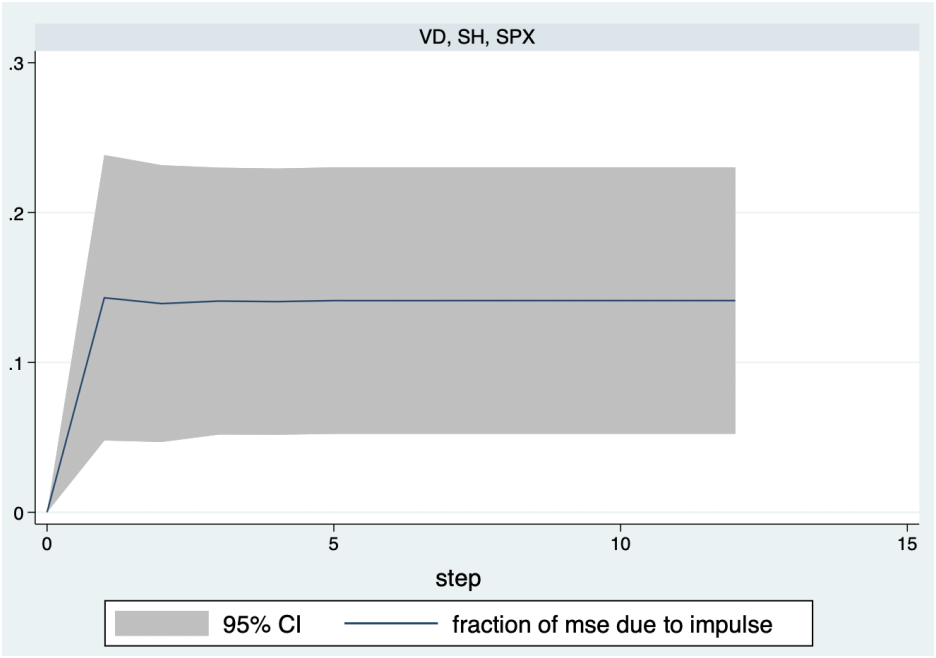


Figure 4. Variance Decomposition of SH

Apart from itself, Fig. 5 show the contribution of another variable. SPX contribute nearly 5%.

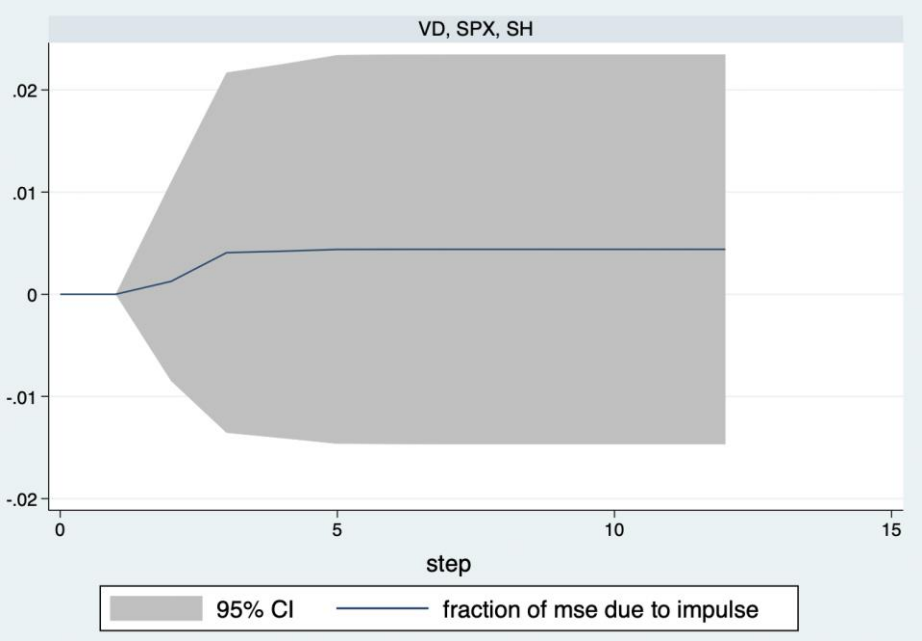


Figure 5. Variance Decomposition of SPX

4. Conclusion

Given the increasing conflicts between China and the U.S., there is a growing need to research the relationship between the Chinese and American capital markets. These two markets have a significant number of investors. In this passage, the return of the SSE index is used to represent the Chinese capital market, while the return of the S&P 500 index represents the U.S. capital market. To examine this relationship, the paper employs a VAR model with an optimal lag. Subsequently, a Granger causality test is conducted, revealing that the return of the S&P 500 index is a significant factor influencing the return of the SSE index. The analysis using IRF suggests that both the SSE index and the S&P 500 index may have reciprocal effects on each other over a five-month period. Additionally, variance decomposition analysis is carried out to assess the contribution of other variables. The weakness of this research might be a lack of considering different index to do the research and comparing the results.

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