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Spillovers in the U.S.-China Stock Markets - A Study of Returns and Volatility under Full Sample Periods and Multi-Special Periods

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Abstract: This paper adopts the ARMA-GARCH model and selects the S&P500 and the SSEC to study the return rate and volatility spillover effect of the US stock market(USM) and the Chinese stock market(CSM) in the full sample period, the Chinese stock market crash in 2015 and the duration when coronavirus spread. In both the full sample period and the two specific periods, it is discovered that the USM significantly increases the return on the CSM. While the CSM barely has any impact on the USM. Although the impact is favorable over the whole sample, it is less pronounced during the The pandemic caused by the novel coronavirus and the China's 2015 stock market debacle. In the whole sample, the S&P500 is unaffected by the SSEC's volatility, whereas the SSEC is significantly harmed by the S&P500's volatility. The S&P500's volatility will have a major beneficial influence on the SSEC, but it won't be communicated from the SSEC to the S&P500 during the global spread of COVID-19. Both of the fluctuation transmission to each other were negligible during the 2015 stock market turmoil. For risk management and stock asset allocation, this study can offer important information to financial institutions, everyday individuals, and governments.

Keywords: return spillover, volatility spillover, Chinese stock market crash, COVID-19 epidemic

1. Introduction

As the process of global economic integration accelerates, financial markets between economies have become more closely linked. This has facilitated the rapid movement and transfer of capital between economies, but may also be accompanied by the phenomenon of financial contagion in the financial markets of various countries, which means that fluctuations in yields and prices in one country's stock market may be associated with fluctuations in yields and prices in the stock market of another country. For this phenomenon, there are currently two main types of doctrines: one is the Economic Fundamentals Hypothesis, which is based on the traditional theory of the complete rationality of investors, and holds that the movements and fluctuations of stock market prices are entirely generated by the fundamentals of the assets, and have nothing to do with the investors. A study by McQueen and Roley found that changes in economic indicators in one country have an impact on future cash flows and discount rates in other countries, which in turn affects the returns on the stock markets of other countries [1]. Gerrits and Yuce pointed out that trade transactions and cooperation among countries have led to the circulation of labor, capital, goods and services among countries, which has led to close financial market linkages among countries. With economic globalization and financial integration, some countries gradually have similar macroeconomic fundamentals, and the volatility of stock market returns and prices may therefore have spillover effects [2]. Another is the Market Contagion Hypothesis, which is based on the theory of imperfect rationality of investors. The hypothesis suggests that when stock market volatility occurs in one country, the noise that triggers the volatility is likely to spread to other countries through various information channels, making it easy for investors in other countries to misjudge their own stock markets. Connolly and Wang find that investors distill unobserved information from a country's stock returns and thus change their investment strategies in other countries, making the returns in each country correlated [3].

Numerous investigations have been done on transference of return and volatility among various equity markets. Huang et al. discovered that developed nations like the United States are always the originator of global stock market risks in the global stock market volatility transmission mechanism by examining the volatility spillovers between the CSM, USM, and the United Kingdom stock market before and after the 2008 financial crisis. Additionally, being a developing market, the CSM is always the recipient of volatility spillover from stock markets in established nations [4]. The SSEC and the DJI trading data from December 12, 2001 to January 23, 2009 were used by Zhang et al. to examine the relationship between CSM and USM. They came to the conclusion that there is no long-run equilibrium relationship between the two markets and that their changes are largely independent of one another. Additionally, the CSM has a modest guiding influence on the USM in terms of price and volatility spillovers [5]. Using volatility data from 16 of the largest stock markets worldwide, Liu et al. looked at the fluctuation connection among nations when coronavirus isn’t under control, and discovered that it considerably increased the volatility spillovers throughout global stock markets [6]. By examining the connections between the equity markets in the whole China area, Johansson and Ljunwall discovered that the average spillover effect from Taiwan had an impact on both Chinese mainland and Hong Kong. The volatility of Hong Kong equity market transmits to Taiwan equity market, which in turn impacts the volatility of the Chinese mainland equity market, is the mechanism for stock volatility across the entire China area [7]. Huo and Ahmed examine the return and volatility spillovers from the Shanghai and Hong Kong stock markets following the introduction of Shanghai-Hong Kong Stock Connect in Chinato provide a basis for the yield transmission and fluctuation connection from Chinese mainland to the Hong Kong stock market [8]. Li and Giles discovered that during both the U.S. subprime crisis of 2008 and the 1997 Asian financial crisis, there were volatility spillovers from the United States to developing countries like China. Additionally, there were spillovers of volatility in both directions between China and the United States when the Asian financial crisis happened [9]. During the the turmoil of CSM in 2015, Imran Yousaf et al. discovered that volatility was spread from USM for most Asian equity markets, with return spillovers from both the U.S. and China for Asian stocks [10].

But Less research has been done on whether and to what extent the yield and price volatility spillovers in the USM and CSM differed in full sample and in the turmoil of CSM in 2015 and the coronavirus pandemic.

In mid-June 2015, the CSM fell 1,000 points in one week. Nearly a month afterward, about 1/2 of stocks in CSM approximately halved in price. Similarly, among the control of coronavirus in 2020, the global stock market fluctuated substantially and the world economy as a whole was in a downward spiral [11].

The purpose of this paper is to investigate the similarities and differences in the spillover effects of returns and price volatility between the USM and CSM under the full sample, during the turmoil of CSM in 2015, and the international health emergency due to the novel coronavirus. The S&P500, which represents the USM, and the SSEC, which represents the CSM, are selected to analyze the spillover Ramification of yield and price volatility of the two in the three periods using the ARMA-GARCH model, and the research in this paper can better explain the transmission impacts of the U.S.-China equity market from the 90s to the present and in the period of the special financial crisis and the global health crisis. This paper can better explain the different transmission effect between the USM and CSM from the 1990s to the present and during the special financial crisis and the global public health crisis, which is of great significance for investors to make stock asset allocation between the USM and CSM.

2. Design of research

2.1. Data sources

In this paper, using Choice Financial Terminal, the daily close prices of the S&P500 and the SSEC are selected as the research objects to reflect the spillover effects of the USM and the CSM. In analyzing this effect in long term between the two, the closing prices of the SSEC from December 19, 1991 to August 22, 2023 are intercepted, i.e., all the data from the base date of the SSEC, therefore, the date chosen for the S&P500 is as also accordingly.

In analyzing the influence of spillovers in the stock markets of the two countries due to short-term extreme events, two sub-samples are selected in this paper. The first sub-sample period is from January 5, 2015 to December 31, 2015, presenting the highly representative financial crisis event 2015 China stock market crash. The second subsample period is December 8, 2019 and December 26, 2022, presenting the just-passed global public health emergency coronavirus outbreak, with the start date of the subsample period being the time of the onset date of the first COVID-19 infection case notified by the Wuhan Health Commission of China, the data cut-off date is the date when the Chinese National Health Commission announced that China will manage COVID-19 with measures against Class B infectious diseases, which means that the Chinese government has basically liberalized the control of COVID-19 outbreak.

2.2. Stability tests

Firstly, the selected time series are subjected to ADF test, i.e. unit root test, whose purpose is to test whether the series are smooth or not. The original hypothesis of ADF test is to assume that the series are not smooth, i.e. the original hypothesis is to be rejected if it is to be proved that the series are smooth. From Table1, it can be seen that the index series are not smooth except the p value of the SSEC series from December 19, 1991 to August 22, 2023 is less than 0.1, while the p value of the yield series in the long term, the period of the COVID-19 epidemic, and the period of the Chinese stock market crash are all 0, which is less than 0.1, so the original hypothesis is rejected, and the three yield series are all smooth.

Table 1: Weak Stationarity Test

	t	p
Index, Overall		
SH 00001	-4.198	0.0045
SP 500	-2.185	0.4981
Index, Covid-19		
SH 00001	-2.127	0.5307
SP 500	-1.201	0.9102
Index, Stock market crash		
SH 00001	-1.741	0.7323

Table 1: (continued).

SP 500	-3.691	0.0229
Return, overall		
SH 00001	-59.000	0.0000
SP 500	-65.230	0.0000
Return, Covid-19		
SH 00001	-18.102	0.0000
SP 500	-18.413	0.0000
Return, Stock market crash		
SH 00001	-11.334	0.0000
SP 500	-11.619	0.0000

2.3. VAR model specification

In (1), US_t is used to represent the return of S&P500, $\alpha_1 + \emptyset_{11}US_{t-1} + \emptyset_{12}US_{t-2} + \cdots + \emptyset_{1p}US_{t-p}$is the autoregressive term, $\beta_{11}CN_{t-1} + \cdots \beta_{1p}CN_{t-p}$ is the autoregressive term for the return of the corresponding SSEC. Similarly, equation (2) is the opposite setting:

$$US_t = \alpha_1 + \emptyset_{11}US_{t-1} + \emptyset_{12}US_{t-2} + \cdots + \emptyset_{1p}US_{t-p} + \beta_{11}CN_{t-1} + \cdots \beta_{1p}CN_{t-p} + e_{1t} \quad (1)$$

$$CN_t = \alpha_1 + \emptyset_{21}US_{t-1} + \emptyset_{22}US_{t-2} + \cdots + \emptyset_{2p}US_{t-p} + \beta_{21}CN_{t-1} + \cdots \beta_{2p}CN_{t-p} + e_{2t} \quad (2)$$

2.4. ARMA-GARCH model specification

Based on this, this paper constructs an ARMA-GARCH model to reflect the volatility of the two markets, and selects the full sample and two special periods to analyze this. Through this analysis, we can have a comprehensive analysis of the changes and similarities of stock volatility in the Chinese and American stock markets in the long term and special periods.

$$R_t = \emptyset_0 + \sum_{i=1}^{p} \emptyset_i R_{t-i} + \alpha_i - \sum_{i=1}^{q} \emptyset_i R_{t-1} \quad (3)$$

$$\varepsilon_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q {\varepsilon_{t-q}}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_p \sigma_{t-p}^2 + \gamma_t n_t \quad (4)$$

In the above equation (3), $\emptyset_0 + \sum_{i=1}^{p} \emptyset_i y_{t-i}$represents the AR(p) model, which stands for the model utilizing the historical returns of the stock market index to predict the future. Meanwhile, the remaining portion$\alpha_i - \sum_{i=1}^{q} \emptyset_i x_{t-1}$ is the MA(q), which represents predicting the future using the error term.

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The GARCH model treats volatility as the variance of the model constructed, and in equation(4), $\alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_q\varepsilon_{t-q}{}^2$ is the ARCH part, $\alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_q\varepsilon_{t-q}{}^2$ is the GARCH part, and $\gamma_t n_t$stands for volatility in another stock market.

3. Empirical results and analysis

3.1. VAR ordering

Table 2 shows the LR test and other information criterion for the VAR model from December 19, 1991 to August 22, 2023, with lag order 12 and lag order 1 in Figure 2 with asterisk sign (*). In order to determine the optimal lag order, comparing the difference in AIC, it can be seen that the difference between lag 11 and lag 12 is about 0.002, and the difference between lag 0 and lag 1 is about 0.02. Therefore, lag 12 is a better choice, i.e., the optimal lag order for the long-run VAR model is 12

Based on the similar VAR ordering method, this paper determines the optimal lag orders for the other two periods during the New Crown epidemic and the Chinese stock market crash, which are order 9 and order 4, respectively.

Table 2: Likelihood ratio test and information criterion

Lag	LL	LR	p	FPE	AIC	HQIC	SBIC
0	42040.3			6.7e-08	-10.8472	-10.8466	-10.8454
1	42089.1	97.642	0.000	6.6e-08	-10.8587	-10.8569*	-10.8534*
2	42094.2	10.322	0.035	6.6e-08	-10.859	-10.856	-10.8501
3	42096.4	4.4042	0.354	6.6e-08	-10.8586	-10.8543	-10.846
4	42107.4	21.968	0.000	6.6e-08	-10.8604	-10.8548	-10.8442
5	42119	23.203	0.000	6.6e-08	-10.8623	-10.8556	-10.8426
6	42131.9	25.785	0.000	6.6e-08	-10.8646	-10.8566	-10.8413
7	42134.8	5.7884	0.216	6.6e-08	-10.8644	-10.8551	-10.8374
8	42142.3	14.893	0.005	6.6e-08	-10.8652	-10.8548	-10.8347
9	42149.6	14.727	0.005	6.5e-08	-10.8661	-10.8544	-10.832
10	42150.2	1.0989	0.894	6.6e-08	-10.8652	-10.8523	-10.8275
11	42152	3.7385	0.443	6.6e-08	-10.8647	-10.8505	-10.8234
12	42163.5	22.894*	0.000	6.5e-08	-10.8666*	-10.8512	-10.8217

After that, a unit root test is also required for whether the selected VAR model is smooth or not, as can be seen from Figure 1, all the roots are within the unit circle, which indicates that the lag order selected for the VAR model in the three periods is appropriate, and there is no need to re-estimate the subsequent order, and VAR (9) is a stable model.

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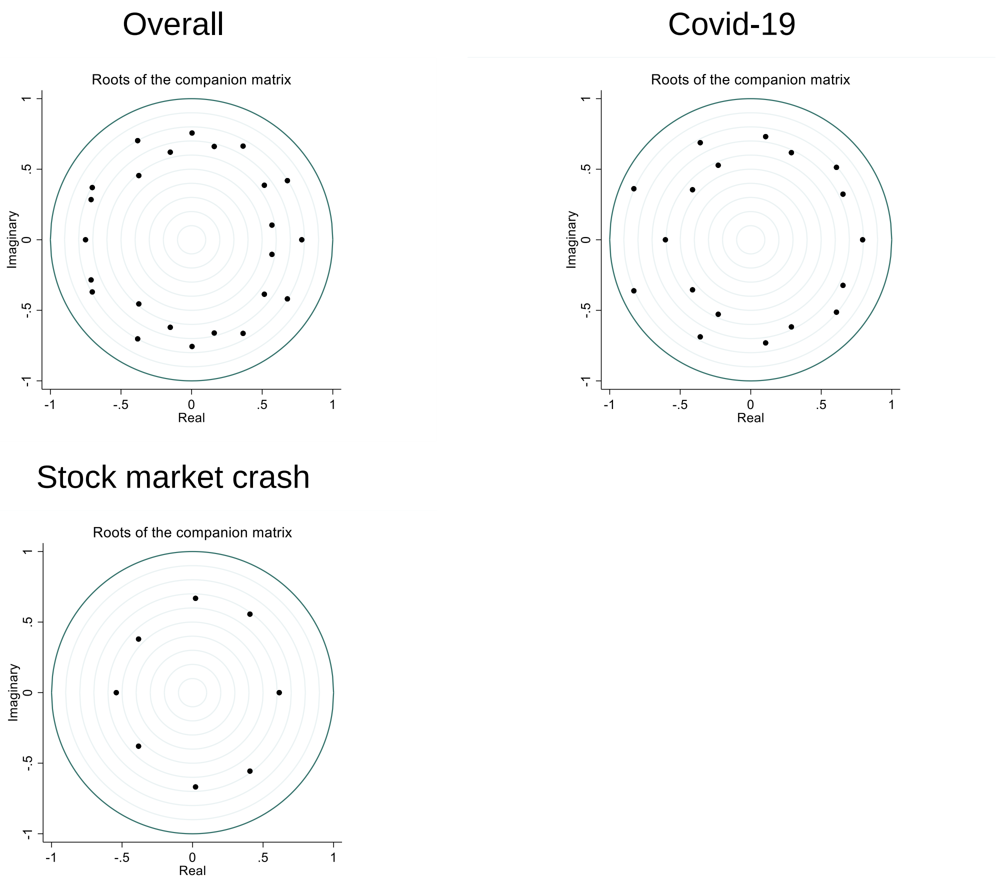

Figure 1: Unit root test

3.2. Impulse response

The impact of one variable’s changes on subsequent changes in another variable is depicted by impulse response graphs. First, the 30-period impulse function is computed and the impulse response function is built using the original VAR model. The impulse response plot of the return series for the whole sample between December 19, 1991 and August 22, 2022 is displayed in Figure 2. The impulse response plot with the SSEC as the response variable and the S&P500 as the impulse variable is displayed on the left-hand side of the figure. With the SSEC acting as the response variable and the S&P500 acting as the impulse variable, the impulse response plots are shown in the left panel. It is clear that the S&P500 return strongly impacts on SSEC, with the S&P500 return having the largest positive impact on the return of the SSEC at about t=2, or about 0.15%. The overall influence is less, close to zero, despite the right-hand figure showing that the SSEC return has a more variable impact on the S&P500 return.

Respond variable: SH 00001 Impulse variable: SP 500

Respond variable: SP 500 Impulse variable: SH 00001

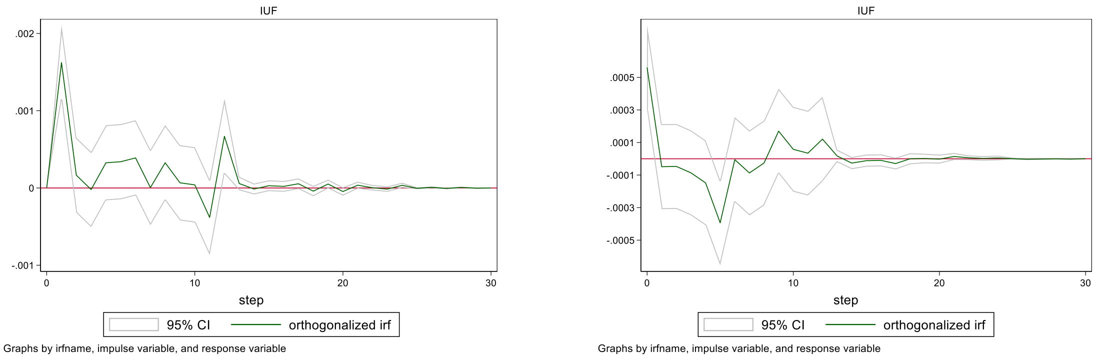

Figure 2: Impulse and response, overall

Similarly, the two plots presented in Figure 3 show the impact of impulse shocks of the two on each other during the era of the coronavirus spread, and it can be observed that the positive shock of the S&P500's return on the return of the SSEC is still large, and that the SSEC also has a positive shock on the S&P500.

Respond variable: SH 00001 Impulse variable: SP 500

Respond variable: SP 500 Impulse variable: SH 00001

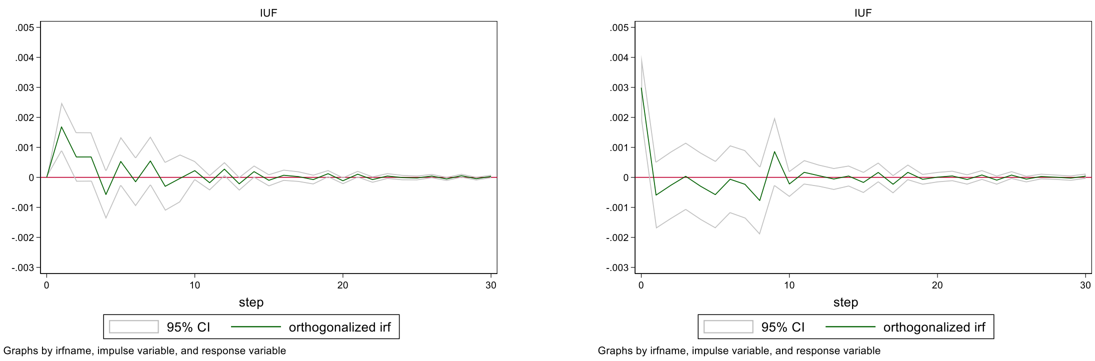

Figure 3 Impulse and response, Covid-19

Figure 4 shows the corresponding impulse plots of the two during the crash. What can be seen from the left-hand side of the graph is that the maximum value of the impulse impact of the return of the S&P500 on the return of the SSEC is 0.4% and lasts for two periods, and although there is a negative impact after that, the overall impulse impact is still a strong positive impact. The right panel shows that when the return of the SSEC is the impulse variable, the overall impact of the impulse on the return of the S&P500 is also positive.

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Respond variable: SH 00001
Impulse variable: SP 500

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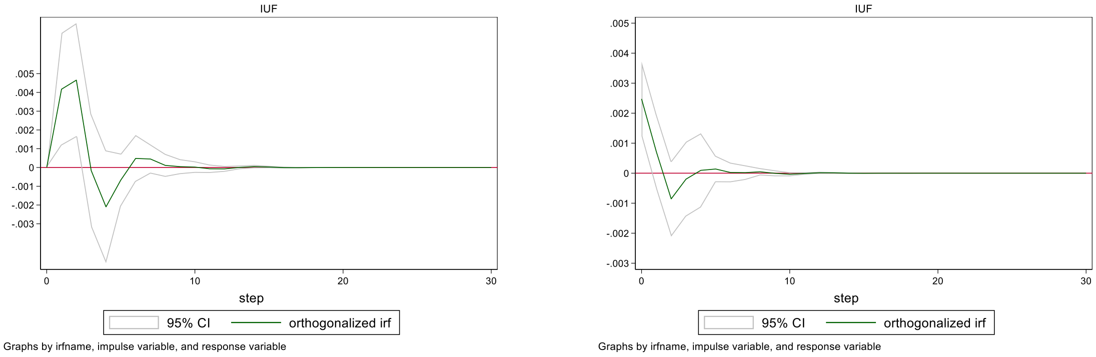

Figure 4: Impulse and response, stock market crash

3.3. ARMA ordering

In this part of the paper, the log-return of the SSEC and S&P500 will be sorted using the PACF and ACF, and Figure 5 shows the fixed-order results presented after sorting. From the image in the first row of Figure 5, it can be seen that the first part beyond the 95% confidence interval is lagged by order 1, so AR(P) is order 1 and MA(q) is also order 1.

From the image in the second row of Figure 5 it can be seen that the first part beyond the 95% confidence interval is also lagged 1st order, therefore AR(P) is 1st order and MA(q) is also 1st order.

PACF ACF

SH 00001

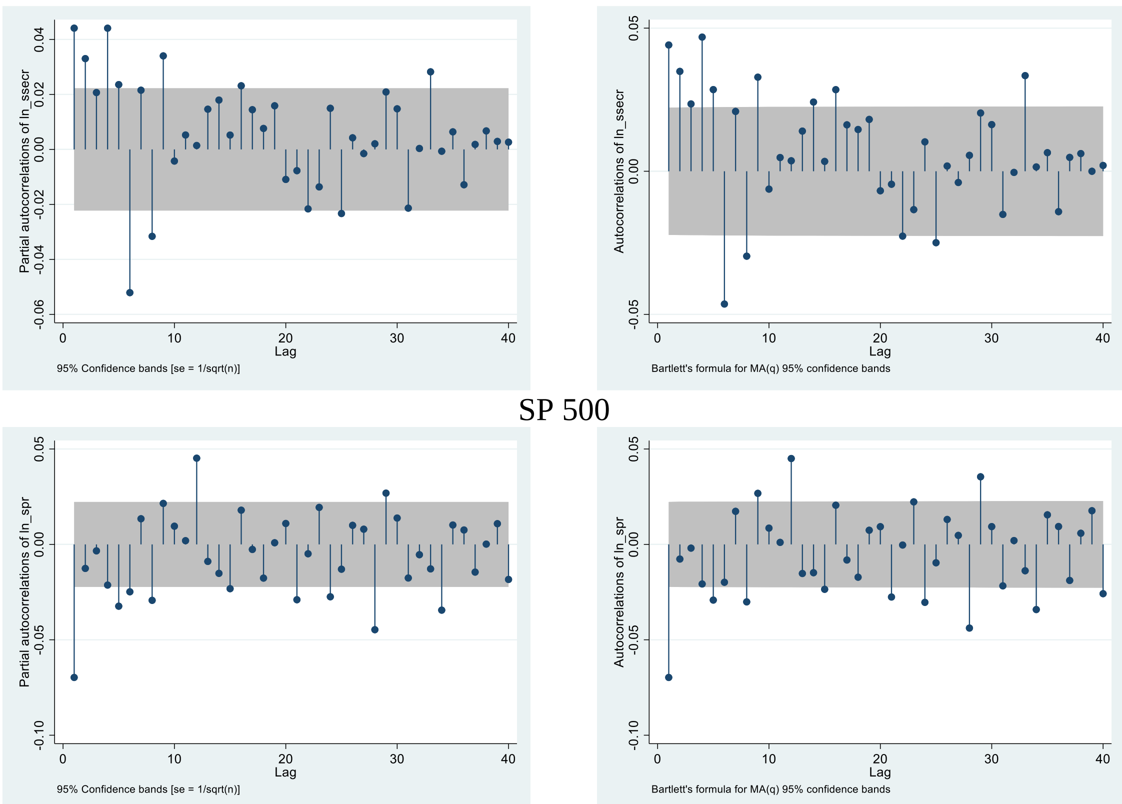

Figure 5: ARMA (p, q) identification, overall

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3.4. ARMA-GARCH estimation results

As shown in Table 3, the p value of the ARCH(-1) and GARCH(-1) terms of the variance equation of the S&P500 and the variance equation of the SSEC in the full sample period are both 0, which implies that there is significant conditional heteroskedasticity in the S&P500 and the SSEC in the full sample.SH 00001-sigma- sq term has a p value of 0.438, which implies that the volatility of the SSEC does not spill over to the S&P500, and SP 500-sigma-sq's p value is 0.042, which is less than 0.1, indicating that the volatility of the S&P500 significantly spills over to the SSEC, and at the same time, because of the coefficient of -21.55416, which indicates that the S&P500's volatility increases, making the volatility of the SSEC decrease.

Table 3: Variance equation, Overall

	(1)			(2)		
	SP 500			SH 00001		
	Coef.	SE	P	Coef.	SE.	P
SH 00001, sigma-sq	-.2825329	.3639395	0.438			
SP 500, sigma-sq				-21.55416	10.58976	0.042
ARCH (-1)	.0999365	.0046334	0.000	.1693895	.00421	0.000
GARCH (-1)	.8864948	.0050008	0.000	.8571572	.0026207	0.000
_Cons	.0006121	.0000656	0.000	.0002477	.0001172	0.035

Similarly, Table 4 shows when COVID-19 rampages, the price volatility of the SSEC had no discernible impact on S&P500, but the fluctuations of the S&P500 had a large positive impact on SSEC.

Table 4: Variance equation, Covid-19

	(1)			(2)		
	SP 500			SH 00001		
	Coef.	SE.	P	Coef.	SE.	P
SH 00001, sigma-sq	-18.79172	40.73452	0.645			
SP 500, sigma-sq				3.190182	1.63769	0.051
ARCH (-1)	.2124085	.0357242	0.000	.24091	.0216838	0.000
GARCH (-1)	.7644734	.0356339	0.000	.4858677	.0496225	0.000
_Cons	.0009194	.0003728	0.014	.0002395	.0004011	0.551

Table 5 shows that in the the turmoil of CSM in 2015, the SSEC's fluctuation was not significantly different with the S&P500's volatility and that the opposite was also true.

Table 5: Variance equation, Stock market crash

	(1)			(2)		
	SP 500			SH 00001		
	Coef.	SE.	P	Coef.	SE.	P
SH 00001, sigma-sq	6.493864	4.209057	0.123			
SP 500, sigma-sq				-755.6231	570.4819	0.185
ARCH (-1)	.2290038	.0653863	0.000	.0524019	.0272868	0.055
GARCH (-1)	.5907308	.11084	0.000	.9033075	.0410831	0.000
_Cons	.0004079	.0005734	0.477	.0018562	.00163	0.255

4. Discussion

According to Chen and Yang's analysis of volatility spillovers between CSM and USM in 2011 using the GARCH model, there were no appreciable fluctuation spillovers between the S&P500, the SSEC, and the Shenzhen Component Index [12]. And this study discovers that over the course of the entire sample period, the S&P500 significantly negatively impacts on the SSEC's volatility. However, during the COVID-19 period, Fluctuations in the S&P500 significantly and positively influence the SSEC.

It has been discovered that despite CSM's fast development, it still has spillover effects from the yield and price volatility of the advanced USM. China should speed up the development of CSM’s mechanism and use stock index futures and other short-selling mechanisms of financial derivatives to increase CSM’s resistance to foreign risk impact. At the moment, we still need to improve attention and early warning to the risk of the USM in order to prevent the USM on the CSM impact being too large. Asian stock market investors require fewer Chinese holdings during the Chinese stock market crash to reduce risk.

5. Conclusion

This paper examines the return spillovers and price volatility spillovers of two stock markets, the SSEC in China and the S&P 500 in the United States, throughout the course of the complete sample period, the turmoil of CSM in 2015, and the era of the coronavirus spread.

Findings indicate that the return rate of the USM has a strong positive impact on the return rate of the CSM during the whole sample period, including the period of the turmoil of the CSM in 2015 and the global spread of COVID-19. The influence of the CSM return rate on the return rate of the USM is virtually zero across the full time, the ramification of the turmoil of the CSM and the COVID-19 period is positive but minor. The S&P500's price volatility has a considerable detrimental impact on the SSEC's volatility, but in the complete sample, the SSEC's volatility does not spill over to the S&P500. During the COVID-19 outbreak, the S&P500's volatility has a considerable positive impact on the SSEC's volatility while the SSEC's volatility has no discernible impact on the S&P500's fluctuations. The S&P500's volatility strongly impacts on the SSEC's volatility whereas the S&P500's fluctuations has no discernible negative impact in 2015 Chinese stock market meltdown. The transmission impact of volatility is likewise negligible.

References

[1] *McQueen, G., & Roley, V. V. (1993). Stock prices, news, and business conditions. The review of financial studies, 6(3), 683-707.*

[2] *Gerrits, R. J., & Yuce, A. (1999). Short-and long-term links among European and US stock markets. Applied Financial Economics, 9(1), 1-9.King, M. A., & Wadhwani, S. (1990). Transmission of volatility between stock markets. The review of financial studies, 3(1), 5-33.*

[3] *Connolly, R. A., & Wang, F. A. (2000). On stock market return co-movements: macroeconomic news, dispersion of beliefs, and contagion. Dispersion of Beliefs, and Contagion (June 2000).*

[4] *Huang, F. X., Kou, L., & Yang, D. L. (2012). Comparison of volatility spillovers between Chinese, British and American stock markets before and after the financial crisis. Mathematical Statistics and Management, 31(4), 751-760.*

[5] *Zhang, B., Fan, Z. Z., & Li, X. D.. (2010). A study on the linkage between Chinese and U.S. stock markets. Economic Research, (11), 141-151.*

[6] *Liu, Y., Wei, Y., Wang, Q., & Liu, Y. (2022). International stock market risk contagion during the COVID-19 pandemic. Finance Research Letters, 45, 102145.*

[7] *Johansson, A. C., & Ljungwall, C. (2009). Spillover effects among the Greater China stock markets. World Development, 37(4), 839-851.*

[8] *Huo, R., & Ahmed, A. D. (2017). Return and volatility spillovers effects: Evaluating the impact of Shanghai-Hong Kong Stock Connect. Economic Modelling, 61, 260-272.*

[9] Li, Y., & Giles, D. E. (2015). Modelling volatility spillover effects between developed stock markets and Asian emerging stock markets. International Journal of Finance & Economics, 20(2), 155-177.

[10] Yousaf, I., Ali, S., & Wong, W. K. (2020). An empirical analysis of the volatility spillover effect between world-leading and the Asian stock markets: Implications for portfolio management. Journal of Risk and Financial Management, 13(10), 226.

[11] Contessi, S., & De Pace, P. (2021). The international spread of COVID-19 stock market collapses. Finance Research Letters, 42, 101894.

[12] Chen, Xiao, & Yang, En. (2011). Leverage and volatility spillovers in US and Chinese stock markets: An empirical analysis based on GARCH model. Financial Science, (4), 17-24.