

# US and China's Stock Markets Correlation of Return and Volatility: Evidence from Time Series Model

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**Abstract.** The US and Chinese economies are highly correlated, and so are their stock markets. This paper applies the vector autoregression model (VAR) to the daily returns of the SSEC and SP500 indexes to estimate their impulse responses to each other and uses ARMA-GARCHX models to examine the relationship between the volatilities of the two indexes. Behavioral finance studies are used to help interpret the results. The research goal is to discover how the two stock markets are correlated in terms of return and volatility spillover effect. It is found that the two markets' returns are positively correlated as shown by positive impacts on impulse response diagrams, meaning they tend to rise or fall together. And there is a one-directional spillover effect between their volatilities, going from SSEC to SP500, which could be due to widespread Chinese investor irrationality and entry limits of Chinese stock markets. In similar correlation-themed research papers usually only volatilities are studied, and this paper fills up a gap by also focusing on return correlation through the VAR model. This paper also uses volatilities as extra explanatory variables in the ARMA-GARCHX models as an innovative method. Suggestions for investors include considering Chinese stock market volatility when evaluating the risks of US stocks and avoiding herding behaviors when making investment decisions. US regulators are recommended to pay special attention to uncertainty in the Chinese market.

**Keywords:** Stock market return, Stock Market Volatility, VAR, ARMA-GARCHX, Spillover Effect.

## 1. Introduction

The Sino-US relationship is one of the most important inter-state relationships in the world. Aided by globalization, the two countries' economies have been closely intertwined through international trade and foreign investments since China's economic reform policies in the 1990s. Although Sino-US decoupling is a trending topic nowadays, its effect on financial markets is still limited [1]. The US wants China to continue purchasing its government bonds and China's RMB with weak convertibility and low global currency share is unable to substitute for the US dollar [2]. Many investors hope to diversify their portfolios by investing in both countries' financial markets. The regulators on both sides are also eager to understand how the other affects their financial market to prevent systematic risks. It is thus necessary to study how the Chinese and US stock markets are correlated in terms of returns and volatilities to make optimal investment decisions and economic policies.

The rest of the paper is organized in the following way: part 2 is a literature review, including relevant research on the correlation between the US and Chinese stock markets and how investor behaviors can cause complications to the problem, with a summary at the end. Part 3 introduces the stock market data used in this paper and proposes a VAR model and ARMA-GARCHX models to analyze the returns and volatilities. Part 4 shows the estimation results of the models of part 3 and their implications on how returns and volatilities of the two stock markets interact. After that, there is a discussion comparing the findings to other papers and suggesting practical uses of this paper. A conclusion is available at the end.

## 2. Literature Review

### 2.1. U.S and Chinese Stock Market Correlation

Many scholars focus on how global events influence the interaction between the Chinese and US stock markets. Jianxu Liu et al. used the ADCC-GARCH model to study the correlation between Shanghai Composite Index and SP500 Index and found that it increased during the COVID pandemic but decreased during the global financial crisis [3]. Mohamed Beraich et al. applied a vector autoregression model on data ranging from June 2019 to June 2022 to calculate volatility spillover effects between Chinese, US, and European financial markets. They determined that the net pairwise volatility spillover effect between the US and Chinese stock markets during the Russian-Ukraine conflict was very small, indicating little connectivity [4]. Other researchers drew conclusions about general trends over the long term. Tianle Yang et al. implemented a TVP-SV-VAR model based on data on US stock volatility, Chinese stock volatility, global oil price, and economic policy uncertainty (EPU) of the two countries from 2003 to 2020 and found that US and Chinese volatilities had positive impulse response to each other over the years [5]. Renhai Hua et al. explored the correlation between NVIX and Chinese stock volatility [6]. NVIX is a novel approach to measure uncertainty in the US stock market by considering the content of the Wall Street Journal and the implied volatility of options [7]. They concluded that NVIX had a significant impact on Chinese stock volatility after China opened its stock market to foreign investors through the QFII and RQFII programs [6].

### 2.2. Irrational Investors and Herding

When investors behave irrationally in the stock market, they make suboptimal decisions about stocks and undermine their returns. Herding behavior is an example of investor irrationality. It can cause market rallies and sell-offs, leading to spikes in volatility which can have spillover effects on other countries' stock markets. It is commonly agreed that Chinese stock investors exhibit significant irrationality. Simon M.S. So examined the daily returns of the six segmented markets on the Chinese stock market and found widespread herding behavior in all of them. The observed herding behavior was more serious when market volatility was high [8]. In comparison, Idibekeabasi Ukpong et al. reached the conclusion that herding did not exist at the market level in the US and only showed up at the industry level to some extent [9]. A reasonable explanation for such findings is that the Chinese stock market is made up of a larger proportion of individual investors than the US stock market, which is dominated by institutional investors. Institutional investors with expertise and rich experience are more likely to make sound decisions instead of following the herd. However, to make matters worse, according to the findings of Shu-Ling Lin et al., not all institutional investors share this trait. US institutional investors use negative feedback strategies against market sentiments while Chinese institutional investors act in the opposite way by embracing positive feedback strategies and fail to suppress market sentiments. As a result, US institutional investors can function as a buffer to reduce herding behavior's effect on stock volatility and stabilize the market while their Chinese counterparts aid herding behavior and further destabilize the market and increase volatility [10].

### 2.3. Review of the literature

Overall, the correlation between the Chinese and US stock markets in terms of volatility spillover has been relatively well researched. However, relatively few papers focus on the correlation between the daily returns of the stock markets or use extra explanatory variables in GARCH models to examine the volatility correlation. Thus, this paper hopes to fill a gap by employing two methods, VAR and ARMA-GARCHX to separately target the impulse response of daily return and volatility spillover effect and combine their findings to achieve a more complete understanding of the relationship.

### 3. Model and Variables

#### 3.1. Data Source

This paper uses Investing.com to obtain the daily closing prices of the Shanghai Composite Index (SSEC) and S&P 500 Index (SP500) from January 4, 2010 to June 30, 2023. SSEC and SP500 represent the overall performances of the Chinese and US stock markets. Daily logarithmic returns are calculated by  $\ln(\frac{P_t}{P_{t-1}})$ ,  $P_t$  being closing price at date t.

#### 3.2. Weak Stationarity Test

A unit root test is required to determine whether the data are stationary or not. According to the ADF test result in Table 1, p-values for the returns of the two indexes are both 0, meaning they are statistically significant. Thus, the original hypothesis that the data are non-stationary can be rejected, and the returns data are stationary.

**Table 1.** Weak Stationarity Test: ADF test

	t	p
	Ln Index	
SSEC	-3.084	0.1101
SP500	-2.840	0.1826
	Ln Return	
SSEC	-39.375	0.0000
SP500	-39.383	0.0000

#### 3.3. Vector Autoregression Model (VAR)

The VAR model is usually applied to establish the dynamic relationship between multiple endogenous variables. In this section, there are two time series variables chosen to build the VAR(p) model: the return of SSEC at time t and the return of SP500 at time t, denoted by  $SSEC_t$  and  $SP500_t$ .

$$SSEC_t = \alpha_1 + \phi_{11}SSEC_{t-1} + \dots + \phi_{1p}SSEC_{t-p} + \beta_{11}SP500_{t-1} + \dots + \beta_{1p}SP500_{t-p} + e_{1t} \quad (1)$$

$$SP500_t = \alpha_2 + \phi_{21}SSEC_{t-1} + \dots + \phi_{2p}SSEC_{t-p} + \beta_{21}SP500_{t-1} + \dots + \beta_{2p}SP500_{t-p} + e_{2t} \quad (2)$$

$$\begin{bmatrix} SSEC_t \\ SP500_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \begin{bmatrix} \phi_{11} & \dots & \phi_{1p} \\ \phi_{21} & \dots & \phi_{2p} \end{bmatrix} \begin{bmatrix} SSEC_{t-1} \\ \vdots \\ SSEC_{t-p} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \dots & \beta_{1p} \\ \beta_{21} & \dots & \beta_{2p} \end{bmatrix} \begin{bmatrix} SP500_{t-1} \\ \vdots \\ SP500_{t-p} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \quad (3)$$

The equations (1) and (2) above are for SSEC return and SP500 return separately, and equation (3) combines them in a matrix form. In equation (1),  $\alpha_1 + \phi_{11}SSEC_{t-1} + \dots + \phi_{1p}SSEC_{t-p}$  is a linear function of SSEC return's past lags, while  $\beta_{11}SP500_{t-1} + \dots + \beta_{1p}SP500_{t-p}$  includes past lags of SP500 return,  $e_{1t}$  being the residue. Consequently, the variable SSEC return is modelled using both its own historical values and past values of SP500 return. The structure of equation (2) is similar to that of (1).

#### 3.4. ARMA-GARCHX Model

Equation (4) shows ARMA model's general expression. AR(p) is embodied in the component  $\phi_0 + \sum_{i=1}^p \phi_i x_{t-i}$ , while the rest of the equation represents MA(q). AR(p) forecasts future returns using past returns, while MA(q) predicts returns with historical error terms.

$$x_t = \phi_0 + \sum_{i=1}^p \phi_i x_{t-i} + \alpha_i - \sum_{i=1}^p \phi_i \alpha_{t-i} \quad (4)$$

After ARMA, this paper builds ARMA-GARCHX models of the returns and volatilities of SSEC and SP500. GARCH (1, 1) is chosen because it reduces the number of parameters and fits well with most time series. This paper uses I. SSEC returns II. SP500 returns III. conditional variances of SSEC

return’s disturbance term IV. conditional variances of SP500 return’s disturbance term (III&IV predicted by ARMA-GARCH models identical to equation (5) except without EEVs) as EEVs, resulting in 4 GARCHX models.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 \sigma_{t-1}^2 + \beta_t EEV(External\ Explanatory\ Variable) \tag{5}$$

In equation (5),  $\alpha_1 \varepsilon_{t-1}^2$  is the ARCH part and  $\gamma_1 \sigma_{t-1}^2$  is the GARCH part.  $\sigma_t^2$  is the conditional variance of the disturbance term of SSEC/SP500. EEV uses returns and conditional variances of SSEC when SP500 contributes to the response variable  $\sigma_t^2$ , and vice versa.

## 4. Estimation

### 4.1. VAR Model Order

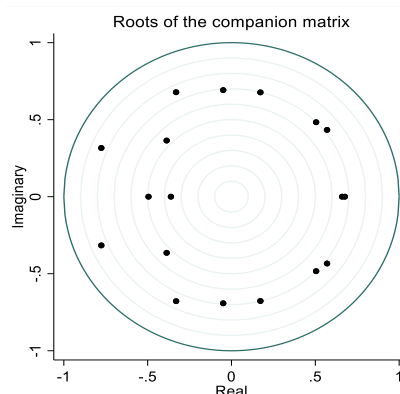
Statistics like LR and FPE should be considered to decide the optimum lag order of the VAR model. The suggested lag orders are followed by an asterisk sign (\*) in table 2.

**Table 2.** Likelihood ratio test and information criterion

Lag	LL	LR	p	FPE	AIC	HQIC	SBIC
0	18865.6			2.2e-08	-11.9579	-11.9565	-11.9541
1	18943.4	155.51	0.000	2.1e-08	-12.0047	-12.0005	-11.9931*
2	18954.2	21.646	0.000	2.1e-08	-12.009	-12.0021*	-11.9898
3	18956.3	4.207	0.379	2.1e-08	-12.0078	-11.9981	-11.9809
4	18963.3	13.952	0.007	2.1e-08	-12.0097	-11.9973	-11.9751
5	18968.6	10.692	0.030	2.1e-08	-12.0105	-11.9954	-11.9683
6	18973.5	9.7601	0.045	2.1e-08	-12.0111	-11.9932	-11.9612
7	18982.2	17.405	0.002	2.1e-08	-12.0141	-11.9934	-11.9565
8	18992	19.668	0.001	2.1e-08	-12.0178	-11.9943	-11.9525
9	18999.3	14.645*	0.005	2.1e-08*	-12.0199*	-11.9937	-11.9469
10	18999.9	1.0953	0.895	2.1e-08	-12.0177	-11.9888	-11.9371
11	19000.3	0.91933	0.922	2.1e-08	-12.0154	-11.9838	-11.9271
12	19002.4	4.2009	0.380	2.1e-08	-12.0142	-11.9798	-11.9182

Lags 1, 2, and 9 have an asterisk sign. LR, FPE, and AIC agree with VAR (9), while HQIC supports VAR (2) and SBIC backs VAR (1). Since VAR (9) has the favor of the majority, combining with the convention that VAR models with small level of lags are usually less desirable, this paper chooses VAR (9) for further analysis.

After the VAR order is chosen, the second test is to check whether the VAR model is stationary. A non-stationary VAR model’s impulse-response function fails to converge to 0 and an increase in return of one index will cause the return of the other index to increase indefinitely, until the whole function system blows up. The unit root test is carried out by drawing the roots and the unit circle. All roots fall inside the circle in Figure 1, thus VAR (9) is a viable model.



**Figure 1.** Unit root test

### 4.2. Impulse Response: Correlation of Return

According to the impulse response diagrams (Figure 2), when the SP500 return increases by 1 percent at  $t=0$ , there is a noticeable positive impact on the SSEC return between  $t=0$  and  $t=4$ , which rises quickly and peaks at about  $t=1$  at approximately 0.22 percent, but then decreases almost as quickly to 0 percent and fluctuates around 0 percent in a zig-zag pattern thereafter. The impact is extremely miniscule after  $t=10$  and virtually non-existent after  $t=20$ . When the SSEC return increases by 1 percent, the initial positive impact on SP500 return peaks at around 0.2 percent at about  $t=0.5$  but quickly decreases to 0 percent at  $t=1$  and stays around 0 percent after that. The impact also becomes very small after  $t=10$  and disappears after  $t=20$ . The two impulse response diagrams have similar overall trends and peaks and indicate that US and Chinese stock market returns are positively correlated, but the positive impact when SP500 is the respond variable wanes much more quickly than when SSEC is the respond variable. It could thus be argued that SP500 is better at recovering from the shocks brought by impulses than SSEC. SP500 prices and returns go back to the market equilibrium level sooner. Several factors may have contributed to this phenomenon: the US stock market is larger in size and has a longer history than the Chinese stock market, so it is more efficient, and the experienced US institutional investors may be better equipped to make reasonable decisions and exert stabilizing influence when stock prices/returns fluctuate.

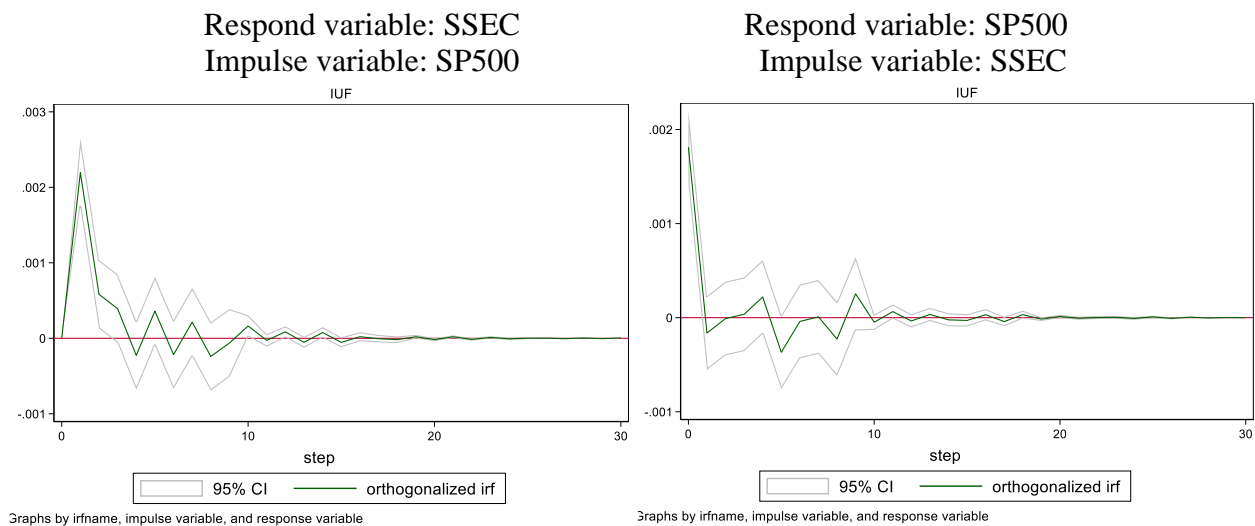
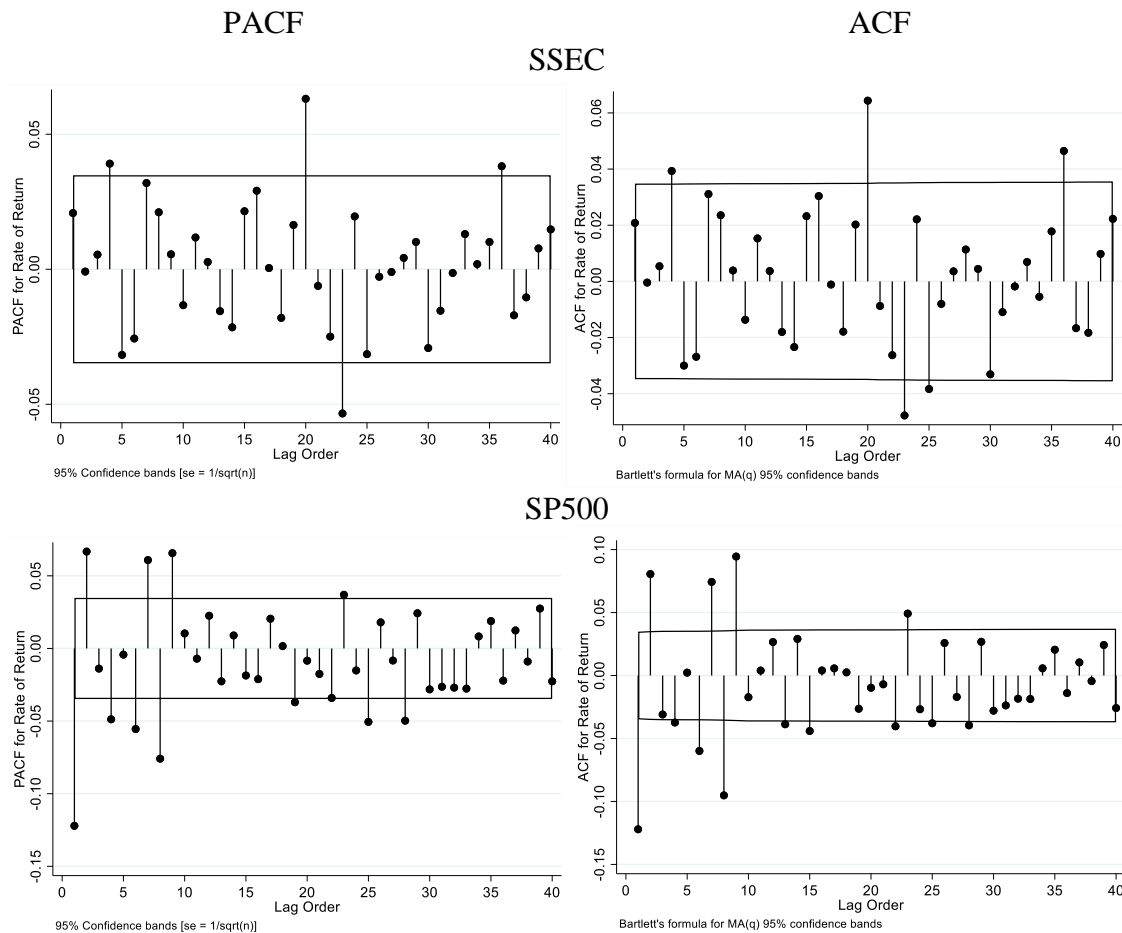


Figure 2. Impulse and response

### 4.3. ARMA Model Order

PACF and ACF are useful in determining the lag orders for  $AR(p)$  and  $MA(q)$ . The results are shown in Figure 3 below.



**Figure 3.** ARMA (p, q) identification

For SSEC, the first value beyond the critical thresholds appears at lag order 4 for both PACF and ACF, suggesting an ARMA (4, 4) model. For SP500, such value appears at lag order 1 for both PACF and ACF, indicating an ARMA (1, 1) model.

#### 4.4. Correlation of Volatility: Spillover Effect

Table 3 highlights the estimation results of the four ARMA-GARCHX models proposed in 3.4 in four separate columns. ARCH and GARCH terms' coefficients in all four columns have p-values of 0, meaning they are statistically significant. Conditional heteroskedasticity is thus present in all 4 instances of ARMA-GARCHX, fulfilling the requirements of the GARCH model. In column 1, SP500 return as an extra explanatory variable has a statistically significant (p=0) negative correlation with the conditional variance  $\sigma_t^2$  of SSEC. In column 2, SP500 volatility has no statistically significant spillover effect (p=0.987) on SSEC volatility. In column 3, there is a statistically significant (p=0) negative correlation between SSEC return and SP500 volatility. In column 4, the coefficient of SSEC volatility is statistically significant (p=0.002), showing that SSEC volatility has positive spillover effect on SP500 volatility, and the magnitude of the coefficient (942.7507) suggests this is a fairly large impact.

To sum up the results, SSEC and SP500 returns have similar negative correlations with each other's volatility, but SP500 volatility tends to not affect SSEC volatility while SSEC volatility has a great spillover effect on SP500 volatility. The negative relationship between one index's return and the other's volatility might be caused by the investors holding onto their current stocks/assets when the domestic market is performing well but selling stocks and transferring capital to foreign stock markets in times of bearish domestic market, thus causing stock prices to fluctuate more in the target foreign market. The differences in volatility spillover effect may be explained by: (1) irrational behaviors among Chinese investors that cause abnormal levels of stock returns and volatility leading

to observable ripple effects in other financial markets (2) the fact that Chinese stock market has tighter restrictions about which foreign investors can buy what kind of stocks (preferring foreign institutional investors who are less susceptible to irrational behaviors), while US stock market does not have such limitations means SSEC might be better shielded from outside volatility influence than SP500.

**Table 3.** ARMA-GARCHX regression: variance equation

	(1)	(2)	(3)	(4)
	SSEC		SP500	
SP500, return	-34.16665			
	(0.000)			
SP500, sigma-sq		-12.12654		
		(0.987)		
SSEC, return			-46.87042	
			(0.000)	
SSEC, sigma-sq				942.7507
				(0.002)
ARCH	0.0648191	0.0637203	0.1591762	0.1663383
	(0.000)	(0.000)	(0.000)	(0.000)
GARCH	0.925759	0.9296222	0.8051211	0.8007404
	(0.000)	(0.000)	(0.0000)	(0.000)
Constant	-13.27472	-13.42814	-12.5897	-12.55944
	(0.000)	(0.000)	(0.000)	(0.000)

## 5. Discussion

Overall, the results of this paper support a one-directional volatility spillover effect between the Chinese and US stock markets (from China to the US), disagreeing with Renhai Hua et al.'s conclusion that US stock volatility has a significant impact on Chinese market volatility. One possible explanation is that NVIX used in their research reflects people's expectations of future volatilities instead of the actual degree of volatility experienced. The results do not fully support Tianle Yang et al.'s finding that the volatility spillover effect is mutual, which could be due to the extra factors that they considered in their VAR model. The results do not contradict or validate the events-focused papers as the interested time spans are different, but it could be argued that long-term correlation trends may be ineffective or reversed in the context of black-swan events.

US stock investors or investors who maintain a portfolio featuring various stocks from both countries should consider this volatility spillover effect in risk management. When the volatility in the Chinese market goes up it might be good for them to reevaluate how much extra risk their US stocks are going to carry and adjust their investment strategies by holding more risk-free assets for example. US policy makers should understand their stock market's susceptibility to turmoil in the Chinese market and devise some buffers. Chinese stock investors, on the other hand, do not need to pay as much attention to uncertainties in the US market as the spillover effect from US stock market is relatively insignificant. But it is beneficial for them to keep an eye on prevalent herding behaviors in the Chinese stock market and plan their investments rationally. Chinese policy makers may try to reduce irrational behaviors through regulations and encouraging financial institutions to take a more responsible role. During negative global events like COVID pandemic all sorts of investors and regulators should be extra cautious as the estimations based on long term data that they usually depend on may be unreliable and the same portfolio may be much riskier.

## 6. Conclusion

The goal of this paper is to explore how the movements in the Chinese and US stock markets are linked in terms of return and volatility, with some help from behavioral finance studies. VAR and ARMA-GARCHX models are utilized to analyze the data, with VAR focusing on impulse responses of the two markets' returns and ARMA-GARCHX studying the risk spillover effects between the markets.

This paper demonstrates that throughout the last decade returns in the US and Chinese stock markets are generally positively correlated, which means they tend to rise or fall together. This is consistent with the fact that stock market performances usually mirror macroeconomic conditions, and the US and Chinese economies are highly connected. The paper also finds through ARMA-GARCHX models that risk spillover effect between the two countries is one directional: Chinese volatility significantly impacts US volatility, but not the other way around. This could be caused by the prevalence of irrational investors in China and the stricter entry limits of the Chinese stock market. Investors and financial regulators of the two countries can make use of these conclusions to reduce their portfolio risks and anticipate incoming stock market shocks by observing each other's stock markets. It should also be noted that stock markets behave unusually during negative global events, diminishing the usefulness of studies based on long term data and creating new challenges.

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