Returns and Volatility in Chinese and U.S. Stock Markets in Uncertain Markets: Evidence from Fed's Monetary Policy

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Abstract. The Federal Reserve announced a 75-basis point rate hike to raise the benchmark rate to a range of 2.25%-2.50% to curb another spike in inflation on July 28. Since 2022, the Fed has announced four rate hikes, with the cumulative increase reaching 150 basis points in June-July alone, the largest since Volcker took the helm of the Fed in the early 1980s, which might be reflected in the volatility of stock prices in China and the U.S. market. This paper assesses the impact of fed rate hikes on the Chinese A-share market, specifically the Shanghai Stock Exchange (SSEC) and Standard and Poor's 500 (S&P 500), a stock market index that reflects the U.S. stock market. A VAR model, and an ARMA-GARCH model were established to analyze the variations in stock prices caused by changes in foreign exchange rate between CNY (China Yuan) and USD (US dollars). As a result, this paper asserts that a more elevated exchange rate has a relatively negative net effect on the Chinese stock market and a negligible influence on the U.S. stock market.

Keywords: Monetary policy; Stock Market; S&P 500; SSEC.

1. Introduction

Since the beginning of the Covid-19 pandemic in 2022, the American administration has undertaken very lenient monetary and fiscal guidelines to rescue the declining economic situation. Regarding the monetary guideline, the U.S. administration briefly lessened the federal funds rate to approximately 0 to 0.25% and enforced massive quantitative easing, expanding the Fed's budget from about four trillion to eight trillion dollars [1,2]. Regarding the fiscal policy, the American federal fiscal deficit amounted to 15% of 2020 annual. The direct stimulus for a such increment is the direct monetary assistance towards low- and middle-income households.

From March 2020-January 2021, the U.S. passed four noteworthy aid rounds programs to mitigate the epidemic's impact: the 2.3-trillion-dollars CARES Act in March 2020, the 484-billion-dollar Wage Protection Plan in April 2020, the 900-billion-dollar Economic Relief Act in April 2020, and the 1.9-trillion-dollar Economic Recovery Act in December 2020 [3]. As a result of substantial monetary and fiscal stimulation, the American economy recuperated quickly from the recession resulting from the pandemic: overall American economy contracted by 3.4% in 2020 but grew by 5.7% in 2021 [4]. In February 2022, the U.S. CPI grew at a year-over-year rate of 7.9%, a peak in 40 years, and the core CPI, excluding energy and food prices, rose at a year-over-year rate of 6.4%, also a record high since 1982; the unemployment rate fell to 3.8% in the same month.

The Federal Reserve declared a 75-basis point rate hike in July 2022, the fourth raising so far in 2022, and proclaimed that there would be further rate hikes at the following two conferences this year. Intending to avert another inflationary spike, the Federal Reserve has announced a 225-basis-point rate hike through July 28, 2022, increasing the benchmark rate around 2.25% to 2.50%.

After the Federal's rate hike announcement, China's foreign exchange and equity markets will gradually develop a phase of falling asset prices and foreign exchange outflows following the CNY devaluation, leading to further CNY devaluation [5]. From April 14 to May 13, 2022, the RMB exchange rate against the U.S. dollar dropped from 6.35 to 6.79, a tremendous reduction of 6.9% in merely one month. The Chinese foreign exchange market's rapid devaluation is unprecedented [6].

Several theories second the existence of a causal association between the stock prices and the exchange rates. This research demonstrates that fluctuations in exchange rates substantially affect stock returns, notably that currency deflation is detrimental to stock market earnings [7]. Using the

EGARCH-X mode, a study of seven industrialized and developing countries found significant proof of a two-sided link between the stock market fluctuations and exchange rate variations [8]. Besides that, a paper discovered considerable bidirectional causation between stock prices and exchange rates by evaluating stock prices and exchange rates for linear and non-linear Granger causality links for twelve emerging market nations [9]. Empirical evidence is generally weak, despite the theoretical literature's suggestion that exchange rates and stock prices are causally related. Most often, for developed nations, the literatures on the relationship between stock markets and exchange rates has produced conflicting evidence of how exchange rates affect stock returns. With the application of the BVAR model, the article suggested an impotent relation exists between the exchange rates and the stock prices in specific emerging markets [10].

All these results demonstrate the complexity of analyzing the influence of exchange rates on global stock markets' performance. Based on this concept, this paper seeks to identify additional correlating relationships between the exchange rate under the fed rate hikes situation to calm down the American economy caused by the stimulus package during COVID-19 and the stock markets of China and the United States.

The subsequent sections of this research are constructed as follows: Part Two consists of the research design, which includes the data sources, definition of rate of returns of stock, unit root test, and model specification; Part Three comprises empirical results based on simulating models from Part Two. Part Four will discuss the parallels and differences between the findings of this research and the other literature and the inference, which will conclude in part Five, of this paper's research

2. Research Design

2.1 Data source

This paper explores the China and United States stock fluctuation with the change in the exchange rate since 2022 under the circumstance of fed rates hike. SSEC and S&P 500 indexes are chosen to represent the stock market in both countries. Initially, the research focuses on the value of stock price and rate of return, which determines the stock market's overall performance. The paper performs an ADF test to examine whether there is an apparent connection between the disparity in the foreign exchange rate and rate of return variables in the circumstance of unstable stock prices and the exchange rate. With the log of the rate of return of all the variables, a VAR model is integrated into a system enhanced over the earlier half of the paper's investigation of such intricate interactions. Additionally, this VAR system can make model-based forecasts of the value of variables. Most crucially, the report illustrates the significance of this model by creating an impulse response graph to show how these interactions in the system interact. The research starts to concentrate on stock price volatility in the paper's final section, which indicates the risk of the stock price in both markets with the exchange rate change by employing an ARMA-GARCH model.

The exchange rate between China Yuan (CNY) and the US dollar (USD) comes from the China Financial Macro Information Database of Choice Financial Terminal. Choice collects crucial information, such as the exchange rates, interest rates, stock price indices, futures and options prices, and details about specific stocks, and updates information daily. In this terminal, the S&P 500 Index is utilized for the American stock exchange, and the Shanghai Composite Index (SSEC) is used for the Chinese one. The closing prices were chosen as a benchmark for the following analysis.

The paper compares stock price data by date to exchange rates and utilizes stock price information from the standard (common) trading days on the Chinese and American stock markets. Furthermore, the research omits exchange rate data on non-trading days.

2.2 Stock return

During the study, this paper initially selects log stock returns, computed as follows:

$$Return\ (SSEC)_t\ == ln(Price\ (SSEC)_t) - ln(Price\ (SSEC)_{t-1}) \tag{1}$$

$Return\ (S\&P\ 500)_t\ == ln(Price\ (S\&P\ 500)_t) - ln(Price\ (S\&P\ 500)_{t-1})$	(2)

The corresponding log return (logarithmic return rate) of both market rate and exchange rate is calculated as:

$Return_{ssec} = ln \frac{rate\ of\ return(SSEC)_t}{rate\ of\ return(SSEC)_{t-1}}$	(3)
$Return_{s\&p\ 500} = ln \frac{rate\ of\ return(S\&P\ 500)_t}{rate\ of\ return(S\&P\ 500)_{t-1}}$	(4)
$Return_{exchange\ rate} = ln \frac{rate\ of\ return(exchange\ rate)_t}{rate\ of\ return(exchange\ rate)_{t-1}}$	(5)

2.3 Unit root test

In time series analysis, tests for stationarity are referred to as unit root tests. According to mainstream economic and finance theory, long-run equilibrium relationships exist among non-stationary time series variables. To transform trending data into static data, researchers could perform unit root tests to decide the order of data differentiation and data regression on deterministic functions of time. In this paper, Augmented Dickey-Fuller (ADF) test is used for testing stationarity. For the testing of non-stationarity, the null hypothesis is calculated at the 1%, 5%, and 10% significance levels. If any series is not stationary, this paper needs to find possible methods to improve the logarithmic results. When doing Unit Root Test, it is usually assumed that the time series xt can be written as:

$$x_t = c_t + \beta x_{t-1} \sum_{i=1}^{p-1} \theta_i \vartriangle x_{t-i} + \xi_t \tag{6}$$

The following Table 1 shows the ADF test results of log stock returns and exchange rate and log returns in both markets and exchange rate.

Table 1 ADF test

Variables	t-statistic	p-value
	Price	
SSEC	-1.9670	0.6194
S&P 500	-2.3680	0.3967
Exchange rate	-3.0550	0.1173
	Return	
SSEC	-8.6230	0.0000***
S&P 500	-7.7760	0.0000***
Exchange rate	-11.0790	0.0000***

It can be found from the results of the ADF test of price and returns that the original data of log stock returns, which is the logarithmic term of SSEC and S&P 500 indexes for both stock markets, and log exchange rate does not show stationarity. The data on the Exchange rate performs better but is still not accountable for a 95% confidence interval. However, when the log return of SSEC, S&P 500, and Exchange rate were token, a noticeable improvement could be outcropped, which suggests that the return of SSEC, S&P 500, and Exchange rate is valid under 99% confidence intervals and thus shows stationarity. Based on these results, the following models in this paper will use this stationary series.

2.4 VAR Specification

2.4.1 Specification

The Vector Autoregression model (VAR model), a commonly used econometric model developed by econometrician and macroeconomist Christopher Sims, is often used in the analysis of multivariate time series models to grab the connection between multiple quantities as they vary from time to time. Also, the Var model provides us with another solution to make the predictions mutually consistent, in addition to using the univariate time series method to predict each variable separately, that is, to fuse all the variables to form a system. In this paper, the log returns of both markets, considered as two variables (y_1, y_2), will be amalgamated with the log return of exchange rate at log term (p=1) and form the following formula with two variables:

$$y_{1,t} = \beta_{1,0} + \beta_{11}y_{1,t-1} + \beta_{12}y_{2,t-1} + \xi_{y_1,t} \tag{7}$$

$$y_{2,t} = \beta_{2,0} + \beta_{21}y_{1,t-1} + \beta_{22}y_{2,t-1} + \xi_{y_2,t} \tag{8}$$

Write the contemporaneous variables as column vectors and combine the corresponding coefficients into a matrix:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} \beta_{1,0} \\ \beta_{2,0} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} \xi_{y_1,t} \\ \xi_{y_2,t} \end{bmatrix} \tag{9}$$

The general formula with multivariable, where Γ_0, Γ_1, …… Γ_p are coefficient matrix for corresponding terms and ψ_t is the error term matrix in time t, can be written as:

$$y_t = \Gamma_0 + \Gamma_1 y_{t-1} + \cdots + \Gamma_p y_{t-p} + \psi_t \tag{10}$$

2.4.2 Impulse response function

The impulse response analysis is a critical measure in econometric studies using VAR models. Their primary goal is to demonstrate how a model's variables change in response to a shock in variables. Therefore, they are precious instruments in the evaluation of economics because of this property, which makes it feasible to follow the propagation of a single shock inside otherwise boisterous equation systems.

To avoid being unable to graphically assess the association between the independent and the dependent variables in this article, since thirty-nine VAR estimators are created by using a twelve-order VAR model with three variables, in this situation, the best tool for examining interactions within or among variables in a VAR system is an impulse response Graph which generally calculated using the following formula:

$$\gamma_s = \frac{\partial \gamma_{t+s}}{\partial {\psi_t}'} \tag{11}$$

According to equation (11), when variable j increases by one unit in the disturbance term at the timestamp t, in the case of other variables and disturbances, remain unchanged, the reaction impact should be the change of the value of variable i in the timestamp t + s. The well-known impulse response function (IRF) is formed from equation (11).

This interaction between variables in a VAR model can be best shown on a graph. A VAR system's impulse responses can all be represented graphically, and these impulse response graphs are crucial for assessing a VAR model.

2.5 ARMA-GARCHX

2.5.1 ARCH

A statistical mode, Autoregressive conditional heteroskedasticity (ARCH) is always used to examine volatility in time series to forecast future volatility. The variance of the disturbance term is taken for granted in conventional econometric models to be constant. However, many economic time series show volatile clustering, and in these situations, it is incorrect to hold the variance constant presumptively. The conditional variance for a time series will vary depending on the information available at different points in the series, and the ARCH model can be used to identify the conditional variance that changes over time. In general, the ARCH(p) model could be written as:

$$\sigma_t^{\,2} = \alpha_0 + \alpha_1\, \xi_{t-1}^{\,2} + \ldots + \alpha_p\, \xi_{t-p}^{\,2} \tag{12}$$

According in equation (12), σ_t denotes the predicted variance during t, ξ_t denotes the actual variance during t, and α_0 is a constant.

2.5.2 GARCH

Every model, including the ARCH model, has constraints. When applied to the short-term autocorrelation operation of heteroskedasticity function, the ARCH model flounders while most of the residual series of financial class data have high-order autocorrelation. Based on the refinement of the ARCH-like measure, a low-order GARCH model can be used to model and lower the estimation of the parameters.

The GARCH model is a regression model designed to analyze the financial data. Such model can model the residual variance further and respond well to the analysis and prediction of volatility and such research plays an essential role in guiding investors' decisions. Normally, GARCH (1,1) can illustrate a considerable quantity of financial time series data with a satisfactory performance in the predictive capacity of unconditional market volatility. The general form of the GARCH(p,q) model is as follows,

$$\sigma_t^{\,2} = \alpha_0 + \alpha_1\, \xi_{t-1}^{\,2} + \ldots + \alpha_p\, \xi_{t-p}^{\,2} + \beta_1\, \sigma_{t-1}^{\,2} + \ldots + \beta_q\, \sigma_{t-q}^{\,2} \tag{13}$$

2.5.3 ARMA-GARCHX

The ARMA model has its limitations in illustrating market volatility. The build-up of an ARMA-GRACH model could more potently analyze the overall volatility of Chinese and US stock market prices using two equations of value and variance, and the GRACH part concentratively summarized market risk.

3. Empirical results

3.1 VAR estimation

3.1.1 Order selection

This paper incorporates three stationary variables into the Vector Autoregression System, including the log return of the SSEC and S&P 500 indexes and the log return of the exchange rate. By experimenting with various VARSOC selection-order criteria in Stata, the proper order of this VAR(p) model is discovered. Table 2 shows the outcome, which indicates that a VAR with one order can be considered.

Table 2 VAR model identification

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	72.2297				.000689	1.23327	1.26128*	1.30222*
1	-58.4955	27.468*	9	0.001	.000638*	1.15566*	1.26769	1.43147

2	-53.8286	9.334	9	0.407	.000685	1.2267	1.42274	1.70936
3	-51.2624	5.1323	9	0.823	.000761	1.33217	1.61223	2.02168
4	-45.4519	11.621	9	0.236	.000803	1.38446	1.74853	2.28083
5	-43.0043	4.8954	9	0.843	.000896	1.49187	1.93997	2.59509
6	-39.705	6.5985	9	0.679	.000987	1.58533	2.11744	2.8954
7	-37.7639	3.8823	9	0.919	.001113	1.70105	2.31718	3.21798
8	-33.0788	9.3701	9	0.404	.001201	1.77178	2.47193	3.49557
9	-26.1253	13.907	9	0.126	.001252	1.80533	2.5895	3.73597
10	-23.532	5.1866	9	0.818	.001403	1.91036	2.77854	4.04785
11	-15.6532	15.758	9	0.072	.001445	1.92874	2.88094	4.27309
12	-12.4666	6.3732	9	0.702	.001612	2.02404	3.06026	4.57524

3.1.2 Model stability

After the establishment of the VAR (1) model, a Wald test is performed to decide the joint significance of the equation and the coefficients of each order of the equation. The results suggest all significant for subsequent testing and zero autocorrelation at lag order. After estimating the VAR model, the eigenvalues were used to determine whether this VAR approach is stable after estimating the VAR model. The outcomes demonstrate that all eigenvalues are inside the unit circle, thus proving such a VAR system is stable. Figure 1 gives us the plotting results of the stability test.

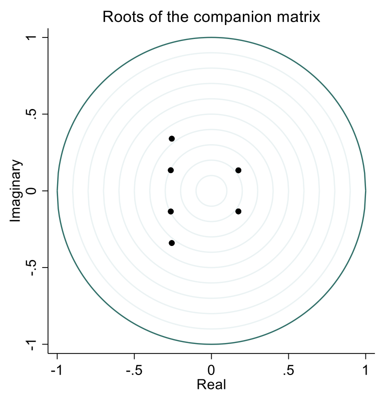

Figure 1 VAR stability

3.2 The Impulse Response

In order to determine how each variable react to the residuals, impulse response graphs proceeded. Figures 2 show the impulse response results for SSEC and S&P500 separately. From the model estimation results, the net effect of an accumulation in exchange rate returns on the Chinese stock market in period t=0 is negative, which suggests that the negative impact of capital outflows directing to a descent in the stock market is more significant than the net effect from exports. The estimated results from the S&P 500 show that a higher exchange rate's impact is insignificant.

SSEC S&P 500

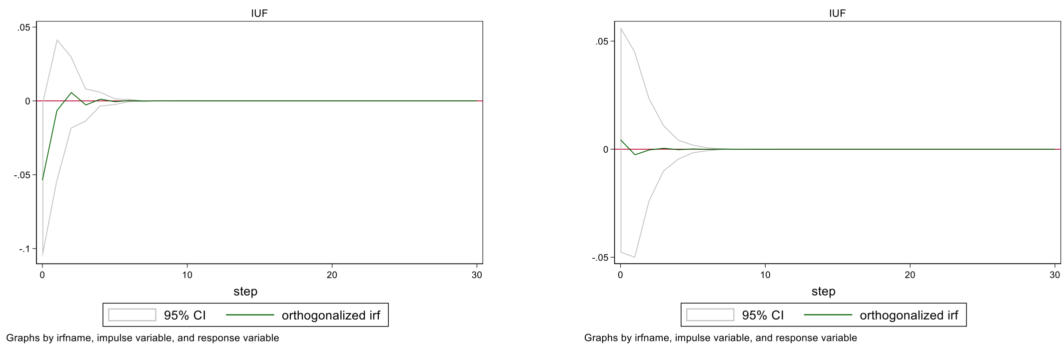

Figure 2 Impulse and response

3.3 ARMA Order Selection

To construct an ARMA model, the paper first determines the appropriate AR and MA parts of SSEC and S&P 500. The autocorrelation plot (ACF plot) and partial autocorrelation plot (PACF plot) of the sequence are drawn in Stata, and the outcomes for the SSEC and the S&P 500 are shown in Figures 3 and 4 respectively.

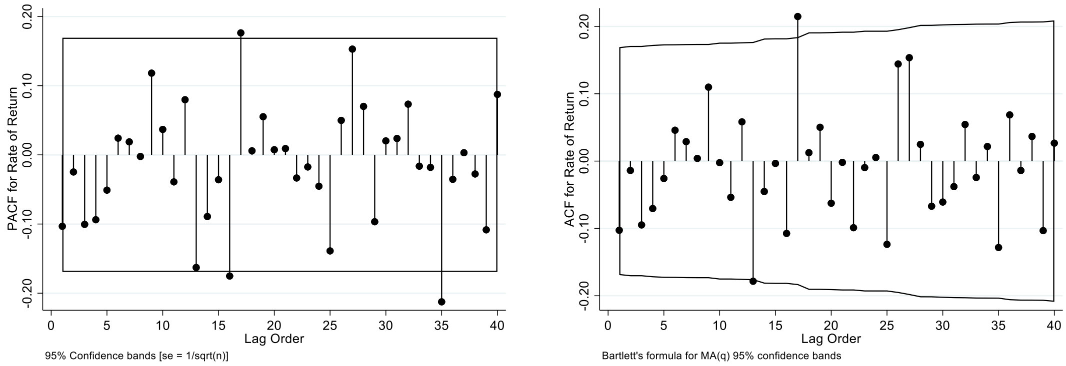

Figure 3 PACF and ACF, SSEC

The black rectangle in the PACF plot is the benchmark for determining the statistically significant term in the AR model, and it can be seen from Figure 3 that the lag 16 and 17 terms of the original series may have a substantial impact on the current data in the case of SSEC. Similarly, lag 9 and 11 terms of the original series may significantly impact the existing data in the instance of the S&P 500 from Figure 4.

For the ACF plot, the black rectangle is the benchmark for the determination of the statistically significant term in the MA model, which suggests that lag 17 of the original series may have a considerable impact on the current data in the case of SSEC from Figure 3 and lag 9 and 11 terms of the original series may have a significant effect on the current data in case of S&P 500 from Figure 4.

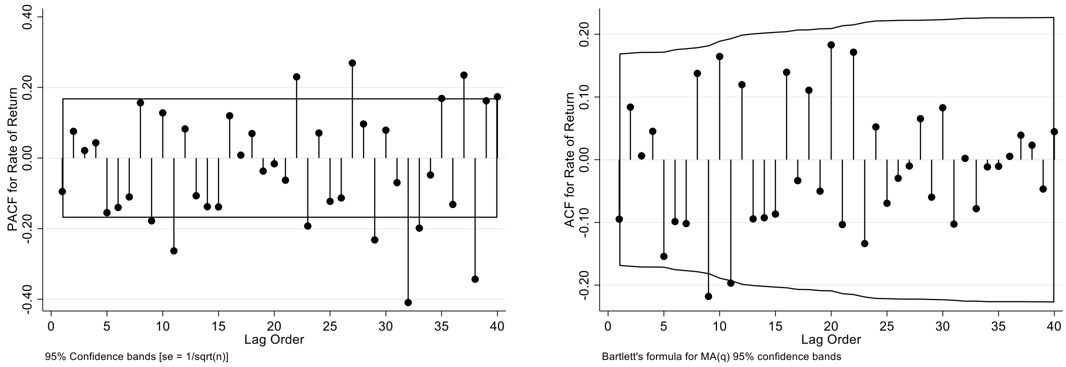

Figure 4 PACF and ACF, S&P 500

3.4 ARMA-GARCHX estimation results

When conditional heteroskedasticity exists in the original series, the GARCH term should be considered. Based on the work done in developing the ARMA model, this paper employs an ARMA (1,1)- GARCH (1,1) model with exogenous lag terms of SSEC and S&P 500 data. As in the previous discussion, this paper is more concerned with the variance equation in the GARCH part, focusing on whether the exchange rate has caused a change in the stock price volatility in both markets, as shown in Table 3.

Table 3 ARMA-GARCH estimation results

Variables	(1) SSEC		(2) S&P 500	
	Coef.	Std. err	Coef.	Std. err

Mean equation				
AR (-16)	-0.1302*	0 .0754		
AR (-17)	0.2618	0.1635		
MA (-17)	-0.1369	0.1597		
AR (-9)			-0.7007**	0.3083863
AR (-11)			-0.1959	0.2492
MA (-9)			0.6357*	0.3313
MA (-11)			0.0226	0.2479
Constant	-0.0026	0.0155	-0.0016	0.0112
Variance equation				
Exchange rate	0.6277	4.8943	2.0510	2.0723
ARCH (-1)	0.7626***	0.1627	0.6382***	0.1211
GARCH (-1)	0.4934***	0.0863	0.4962***	0.1152
Constant	-6.0738***	0.5248	-6.2232***	0.9588

From the estimation results of ARMA-GARCH, the ARCH and GARCH terms of the models in columns (1) and (2) are significant, indicating that there is substantial conditional heteroskedasticity in both the SSE and S&P 500 returns, thus allowing for GARCH modeling. However, the coefficient on the log returns of the exchange rate is not significant, indicating that modifications occurred in the exchange rate do not increase the daily volatility of both American and Chinese stock markets. Although such shock did not cause market volatility (dramatic changes), it led to a downside.

4. Discussion

As was previously indicated, the results of the impulse response graph for the two countries suggest that the association between the exchange rates and the stock prices is slightly distinct. Higher exchange rate returns negatively affect the Chinese stock market, as capital outflows resulting from stock market falls are more significant than the exporters' net effect. The findings are consistent with the article, utilizing the Shanghai Campsite Index from 2005 to 2017, discovering only a short-term influence that the appreciation of CNY will have on business profits via imports and exports, altering stock values and finding a negligible long-term effect on the stock market [11]. The anticipated S&P 500 index results show that rising exchange rates have no comparable effect.

The ARMA-GARCH model finds that the coefficient on the exchange rate's log return is insignificant, indicating that exchange rate changes do not increase the daily volatility of the U.S. and Chinese stock markets. The S&P 500 index manifests no long-term stable equilibrium link between the exchange rate and stock prices. Furthermore, the Chinese stock market also shows no average spillover effect between the foreign exchange and stock markets, which coincides with the evidence of this insignificant relationship in research done in 2010, trying to find the relationship between foreign trade and the stock price of the Chinese stock market with trading data from 1991 to 2009 [12].

Further research can be conducted in two ways. First, due to the effect of inflation in 2022, the CPI and PPI indexes can be added to the analysis, and other exogenous variables such as import and export data or trade deficit can be included to investigate further whether these exogenous conditions affect our study. Second, additional market indicators such as Shenzhen Stock Exchange Component Index (SHE) and the Dow Jones Industrial Average (DJIA) can be added to similar models to reduce the limitations and stochasticity of using only two indicators to explore the association of the exchange rates and the market prices more precisely.

5. Conclusion

According to the theoretical analysis, the Fed's rate hike will inevitably lead to higher demand for dollars from international lenders and financial markets and higher exchange rates. However, the impact of the higher exchange rate on the firm has two effects. With the assumption that there is rigidity in the short period of the firm's product price, which is difficult to adjust, the U.S. stock market has many globally operating firms, but the significant revenues and financial reports are denominated in U.S. dollars. A stronger dollar means that firms' operating income abroad will depreciate; from this aspect, the Fed's interest rate hike may harm local firms. Nevertheless, the international financial markets hold more in dollars, and this money may flow into the stock market or bond market, increasing the demand for stocks. In the case of the Chinese stock market, similarly, although there will be a partial outflow of funds, it will also increase the volume of exports, hence augmenting business profits and stock prices. Based on the above analysis, it is impossible to directly determine the net effect of the Fed's rate hike on the Chinese and U.S. stock markets.

The Foreign Exchange Rate has only an insignificant effect on Chinese and US stock market prices in this research. This paper finds a quantitively association of the exchange rates and the market prices. With the premise of the rate of stock return based on rigidity in the short period of the firm's product price and omitting another potential outside variable that impact the general stock markets, the research results confirmed previous conjectures and some theoretical judgments, which show a slightly negative net effect caused by a higher exchange rate on the Chinese stock market and a negligible influence on American stock market.

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