The Time-varying Impact of the European Central Bank's Interest Rate Policy on China's Stock Market

Yicheng Wang

Shanghai Jiao Tong University, Shanghai, 200240, China

wyc123456@sjtu.edu.cn

Abstract. To curb the inflation, the European Central Bank (ECB) said to raise interest rate, which is the biggest since the physical euro currency was introduced in 2002. Depending on some studies, monetary events, such as increasing interest rate, may have spillover effects on stock markets, as well as impact on returns of stock markets. In order to figure out the correlation between Euro appreciation and the performance of Chinese stocks, the article constructs VAR model based on Euro Index (EI), Shanghai Securities Composite Index (SSEC), and Shenzhen Securities Component Index (SZSE). Furthermore, the article constructs ARMA-GARCH model based on volatilities of SSEC and SZSE, introducing volatility of EI as external explanatory variable. The article finds that the impact of Euro appreciation on the return rate of SSCE and SZSE will show positive and negative alternating results in the future, while the net impact is positive. Moreover, from the empirical result of GARCH model, the volatility spillovers of EI on SSEC and SZSE are confirmed.

Keywords: Euro Index, Shanghai Securities Composite Index, Shenzhen Securities Component Index, Euro appreciation, Volatility spillover.

1. Introduction

1.1. Background

The European Central Bank (ECB) said to raise all three key eurozone interest rates by 75 basis points at its monetary policy meeting on September 8 2022, and said it may continue to raise rates to further curb inflation. It was the biggest increase since the physical euro currency was introduced in 2002. The increase of interest rate of ECB will lead to the appreciation of Euro, influencing monetary market, especially the stock market. In the article, the author focuses on how appreciation of Euro will act on Chinese stock market. SSEC and SZSE are introduced to present its performance.

Shanghai Securities Composite Index (SSEC) selects all the stocks listed on the Shanghai Stock Exchange, including A shares and B shares, as the sample stocks. It has been issued officially since July 15, 1991. Shenzhen Securities Component Index (SZSE) selects 500 representative listed companies as sample stocks, prepared by using the number of free circulating shares of the sample stock as the weight. It takes July 20, 1994 as the base period, with a basis point of 1000.

To measure the appreciation and devaluation of Euro, Euro Index is adopted. The base period of the Euro index is December 31, 1998, and the five most liquid currencies --US dollar (USD), British pound (GBP), Japanese yen (JPY), Swiss Franc (CHK) and Swedish krona (SEK) -- are selected as the sample currencies. The weight of each currency is determined based on three main factors: 40% of each economy's bilateral trade with the euro area, 40% of each economy's money supply M, and 20% of each economy's gross domestic product. The index weights are at 44.28% for USD, 24.91% for GBP, 21.55% for JPY, 6.29% for CHF and 2.98% for SEK.

1.2. Literature Review

Much empirical research has been done to figure out how monetary events impact on stock market. Jung Wan Lee, Tian yuan Frederic Zhao proofed that causality from parities to stock prices exists in a long term in Chinese stock markets. Moreover, they reveal that causality from Korean won and Japanese yen parities to the returns of Chinese stock markets exists in a short term [1]. Woan Lin Beh reveals that in the long term, exchange rate is one of the crucial factors to U.S. stock market. Meanwhile, Chinese stock markets have both long- and short-term relationship with macroeconomic factors in U.S. [2]. Haian Chen and Di Hu find that the interdependence between stock returns and interest rates exists in China. However, the degree of interaction in China is much smaller than that in U.S., which means adjusting interest rates is not effective to regulate and control the whole monetary environment [3]. Jing Zhang and Ya ming Zhuang find that U.S. stock markets have high volatility spillovers to Chinese stock markets [4]. Gang Jin Wang, Chi Xie, Zhi Qiang Jiang, and H. Eugene Stanley find that the volatility spillovers of stock markets are the greatest, followed by the bond market, while the commodity future markets and the FX are receivers of the spillovers. Meanwhile, the volatility spillovers are time-varying, influenced by big financial events [5].

In a brief, stock market has been proofed to be related to monetary factors including interest rate, export value and exchange rate. Meanwhile, Chinese stock market has been proofed to have a certain relationship with Japanese yen and Korean won exchange rate, as well as American stock markets. Moreover, stock market has been proofed to have strong volatility spillovers to FX, but how FX impacts on stock markets requires further study. Based on the above, this article tries to figure out the relationship between Chinese stock markets and Euro Index.

2. Research Design

2.1. Data Source

From https://cn.investing.com/, Europe Index (EI), Shanghai Securities Composite Index (SSEC) and Shenzhen Securities Component Index (SZSE) are downloaded. The author chooses data from 2020-9-16 to 2022-9-16, in order to avoid the impact of the pandemic. In this paper, closing prices are sorted by date and numbered by positive integer (noted as 'time') from the past to the present. Then closing prices become a time series data related to 'time', with 486 periods. Moreover, data is transferred by the formula ln(1+x) to keep time series data stationary. Stata is used to process the data and construct models.

2.2. Augmented Dickey–Fuller (ADF) Unit Root Test

ADF is used to test whether time series data are stationary or not. The first 3 lines in Table 1 is ADF test on original data transferred by ln(1+x). Their p-values are far bigger than 0.1, indicating that the time series isn't stationary. The last 3 lines in Table 1 is ADF test on the differences of transferred data. Their p-values are all equal zero, which means their stationarity is significant. Thus, the model built in them will be feasible.

Table 1. ADF test

Variables	t-statistic	p-value
	Index	
SSEC	-2.583	0.2876
SZSE	-2.312	0.4275
EURO index	-2.665	0.2507
	Yield	
SSEC	-15.206	0.0000***
SZSE	-15.385	0.0000***
EURO index	-15.957	0.0000***

2.3. Vector Autoregression (VAR) Model

As is mentioned above, this article tries to figure out how SSEC and SZSE act on EI. Here VAR model is introduced. [6] VAR puts variables together and forecasts as a system so that the forecast is mutually consistent. VAR model is not based on economic and finance theory, so other explanatory variables can be added arbitrarily to a certain extent. In this article, three separate time series variables, as mentioned in 2.1, SSEC, SZSE and EI, are chosen to construct VAR(p) model, denoted by $x_{t,1}, x_{t,2}, x_{t,3}$.

$$\begin{pmatrix} x_{t,1} \\ x_{t,2} \\ x_{t,3} \end{pmatrix} = \begin{pmatrix} d_1 \\ d_2 \\ d_3 \end{pmatrix} + \sum_{i=1}^{p} \begin{pmatrix} a_{1i} & b_{1i} & c_{1i} \\ a_{2i} & b_{2i} & c_{2i} \\ a_{3i} & b_{3i} & c_{3i} \end{pmatrix} \begin{pmatrix} x_{t-i,1} \\ x_{t-i,2} \\ x_{t-i,3} \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{pmatrix} \quad (1)$$

The equation (1) is supposed to show EI's impact on SSEC and SZSE. To clarify, in equation (1), $\sum_{i=1}^{p} a_{1i}x_{t-i,1}$ represent p order lag of SSEC, $\sum_{i=1}^{p} b_{1i}x_{t-i,2}$ represent p order lag of SZSE, and $\sum_{i=1}^{p} c_{1i}x_{t-i,3}$ represents p order lag of EI. d_1 is the constant term and ε_1 is the error term. The rest are in the same way.

2.4. ARMA-GARCH Model

$$x_t = a_0 + \sum_{i=1}^{p} a_i\, x_{t-i} + \varepsilon_t - \sum_{j=1}^{q} b_j\, \varepsilon_{t-j} \quad (2)$$

In equation (2), x_t represents $x_{t,1}, x_{t,2}$ or $x_{t,3}$, and ε_t is the error term of x_t. $a_0 + \sum_{i=1}^{p} a_i\, x_{t-i}$ (AR(p)) represent p order lag of x_t, and $\varepsilon_t - \sum_{j=1}^{q} b_j\, \varepsilon_{t-j}$ (MA(q)) represent present disturbance and q order lag of disturbance. In ARMA, values (AR(p)) and disturbances (MA(q)) are used to predict the future at the same time [7].

$$\sigma_t^2 = a_0 + \sum_{i=1}^{p} a_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} b_i \sigma_{t-i}^2 \quad (3)$$

In equation (3), $a_0 + \sum_{i=1}^{p} a_i \varepsilon_{t-i}^2$ (ARCH(p)) represent p order lag of disturbance and $\sum_{i=1}^{q} b_i \sigma_{t-i}^2$ (GARCH(q)) represent q order lag of variance. Engle (1982) pointed out that time series data exist a special heteroskedasticity, called 'Autoregressive Conditional Heteroskedasticity', denoted as ARCH. To process data with this heteroskedasticity, in GARCH model, disturbances and variances are used to predict future variance at the same time. To some extent, GARCH (1,1) is equivalent to ARCH(p) [8], while it requires fewer parameters, so in this article, GARCH (1,1) is introduced.

3. Empirical Result and Analysis

3.1. Order of VAR Model

To determine the order of VAR model, LR criterion is introduced here. [9] From Table2, in the LR column, the number in 19th and 21st line are the biggest. Here 21 is chosen as the order of VAR.

Table 2. VAR model identification

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	5141.77				4.2e-14*	-22.294*	-22.2834*	-22.2671*
1	5147.54	11.545	9	0.240	4.2e-14	-22.28	-22.2376	-22.1724
2	5153.56	12.036	9	0.211	4.3e-14	-22.2671	-22.1929	-22.0788
3	5157.7	8.2835	9	0.506	4.4e-14	-22.246	-22.1401	-21.977
4	5160.94	6.4776	9	0.691	4.5e-14	-22.221	-22.0833	-21.8713
5	5163.64	5.4087	9	0.797	4.6e-14	-22.1937	-22.0242	-21.7633
6	5169.76	12.232	9	0.201	4.7e-14	-22.1812	-21.9799	-21.6701
7	5175.62	11.716	9	0.230	4.7e-14	-22.1675	-21.9345	-21.5758
8	5182.09	12.951	9	0.165	4.8e-14	-22.1566	-21.8918	-21.4841
9	5186.34	8.486	9	0.486	4.9e-14	-22.136	-21.8394	-21.3828
10	5192.76	12.846	9	0.170	4.9e-14	-22.1248	-21.7964	-21.2909
11	5197.24	8.9677	9	0.440	5.0e-14	-22.1052	-21.7451	-21.1906
12	5200.32	6.1458	9	0.725	5.2e-14	-22.0795	-21.6876	-21.0842
13	5204.65	8.6731	9	0.468	5.3e-14	-22.0592	-21.6356	-20.9833
14	5210.25	11.202	9	0.262	5.4e-14	-22.0445	-21.5891	-20.8879
15	5217.63	14.748	9	0.098	5.4e-14	-22.0374	-21.5502	-20.8001
16	5219.41	3.5548	9	0.938	5.6e-14	-22.0061	-21.4871	-20.6881
17	5226.34	13.868	9	0.127	5.6e-14	-21.9971	-21.4464	-20.5984
18	5232.8	12.91	9	0.167	5.7e-14	-21.9861	-21.4036	-20.5067
19	5241.45	17.314	9	0.044	5.7e-14	-21.9846	-21.3703	-20.4245
20	5243.22	3.5429	9	0.939	5.9e-14	-21.9532	-21.3072	-20.3124
21	5251.86	17.268*	9	0.045	5.9e-14	-21.9517	-21.2738	-20.2302
22	5255.64	7.5595	9	0.579	6.0e-14	-21.929	-21.2194	-20.1268
23	5261.38	11.48	9	0.244	6.1e-14	-21.9149	-21.1735	-20.032
24	5265.23	7.7139	9	0.563	6.3e-14	-21.8926	-21.1194	-19.929

After determined the order of VAR, it's necessary to verify whether the VAR model is stationary or not. In Figure 1, all the roots are in the unit circle, which indicates that VAR model is stationary.

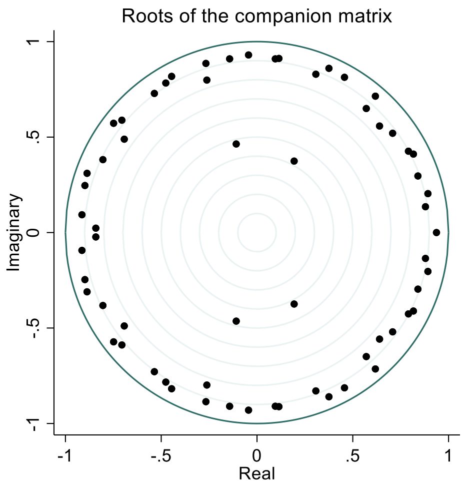


Figure 1. VAR stability Photo credit: Original

3.2. Impulse Response

The European Central Bank raised interest rates for the first time in 11 years in July. The appreciation of Euro caused by the interest rate increase will inevitably cause capital flows. The international capital market and international floating funds will increase their holdings of euro due to the interest factor. This behavior may lead to following economic consequences.

First, the increase of international capital holdings of euros may cause a large amount of euros to flow into the European stock market or bond market, which means that there will be a net capital inflow of EU member countries, and conversely, there will be a net capital outflow of other countries. Net capital outflow has a negative impact on China's stock market.

Second, the appreciation of the euro means an increase in its purchasing power, which will be good for EU countries' imports and bad for their exports. But for China, it will be good for Chinese companies' exports. As the world's factory, China has long relied on exports to prop up its economy. Therefore, the appreciation of the euro is likely to have a positive market feedback.

Thirdly, interest rate increase means the rise of interest rate. As a contractionary monetary policy, an inevitable result is the increase of savings and the decrease of consumption. The direct result of this condition is the decrease of consumption in EU countries, which may also be transmitted to the export volume of Chinese enterprises.

To sum up, it is impossible to directly infer which of the above effects is dominant from theoretical analysis.

SSEC SZSE

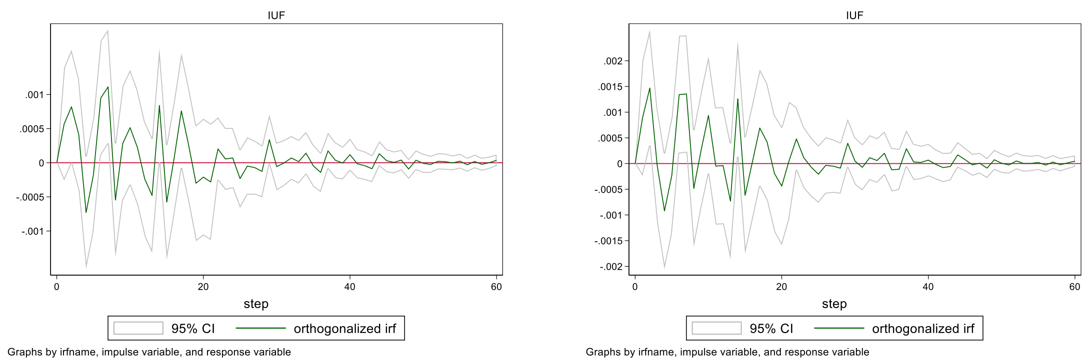


Figure 2. Impulse response

Photo credit: Original

Impulse response diagram is to show how one standard deviation shock at time t will impact on time $t+s$, which s is the 'step' in Figure 2. Cumulative effect function is to add the impact on time 1, 2, 3…… t together, in order to measure the cumulative effect of one standard deviation shock at time t [10].

From Figure 2, this part can basically judge that the impact of euro appreciation on China's stock market is positive. Specifically, in the period of $s=0$, if the euro return rate increased by 1 unit, the impact on the return rates of SSEC and SZSE will show positive and negative alternating results in the future. However, both the size and frequency of the positive effect were larger than the negative effect. For example, the highest and second highest values of the positive effect were about 0.1% and 0.075%, while the highest and second highest values of the negative effect were about -0.075% and 0.05%, respectively. As far as the time effect is concerned, the shock of the current period starts to fade away around period 30.

SSEC SZSE

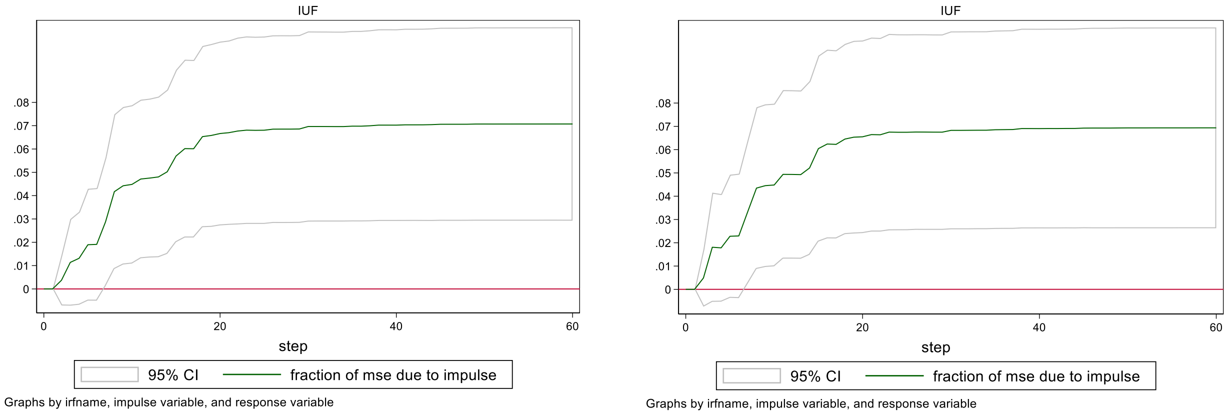


Figure 3. Cumulative response

Photo credit: Original

It is hard to judge the net effect of euro appreciation on Chinese stock market from impulse response graph alone. Accordingly, this paper further calculates the cumulative effect function. It can be seen from Figure 3 that after 60 periods of cumulative impact, the net impact on the Shanghai stock market and Shenzhen stock market is about 7% and 6.5%, respectively. The probable reason for the greater impact on Shanghai is that the Shanghai Stock Exchange has a larger volume and more large enterprises that rely on import and export trade.

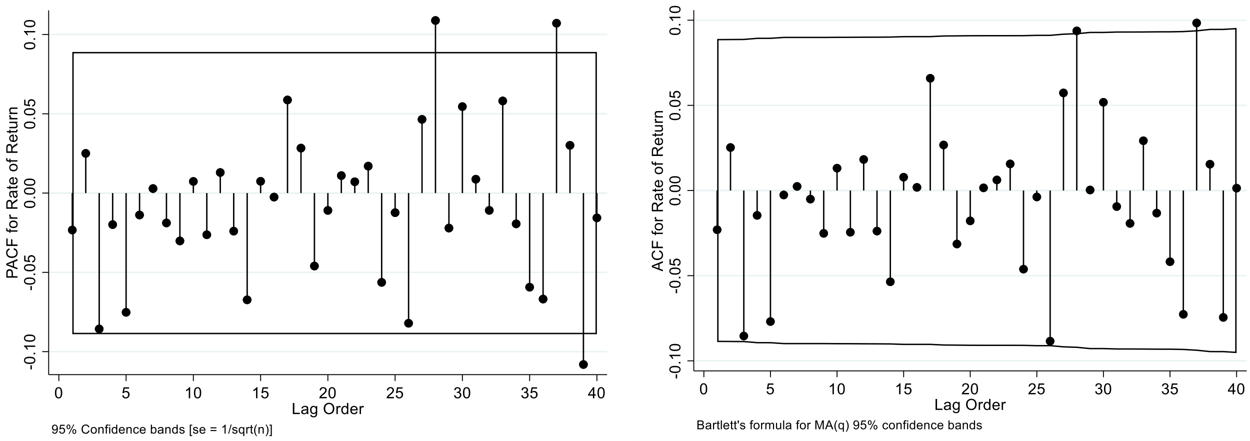
Based on the above empirical results, this paper believes that the export effect caused by euro appreciation plays a dominant role.

3.3. ARMA Specification

PACF and ACF are introduced to determine the lag order of ARMA [11]. In the SSEC part of Figure 4, the first part beyond the critical values is 28 for both PACF and ACF plots, which indicates that ARMA for SSEC and EI should be ARMA (28,28). In the SZSE part of Figure 4, there is no part beyond the critical values, which indicates that ARMA is not fit for constructing model between SZSE and EI.

PACF ACF

SSEC



SZSE

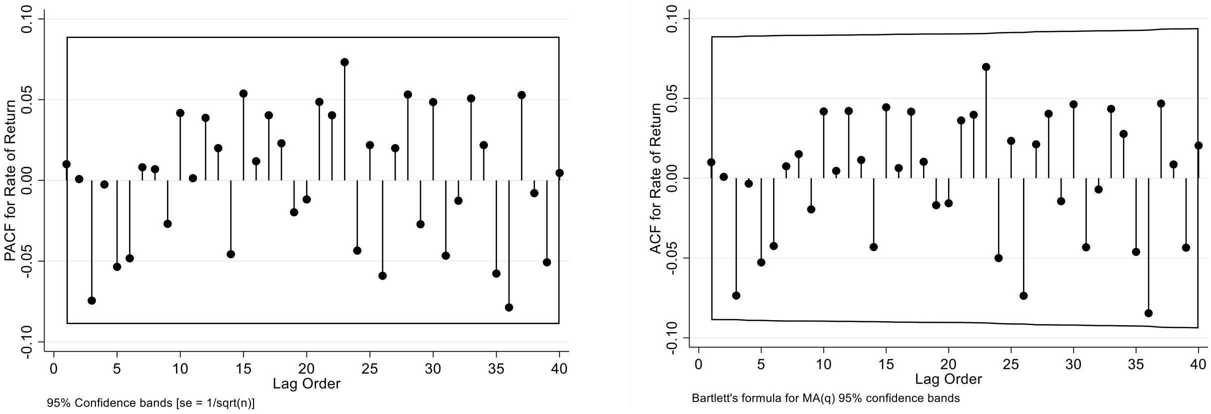


Figure 4. PACF and ACF

Photo credit: Original

3.4. ARMA-GARCH Estimation Results and Variance Equation

Figure 5 is the time series diagrams of returns of SSEC and SZSE. Obviously, the returns of SSEC and SZSE have aggregation and ARCH, but whether this effect is significant still needs further empirical test. As mentioned in 2.4.2, GARCH is introduced to process time series data with conditional heteroskedasticity and predict future risks by variance equation. Thus, GARCH model is fit for SSEC and SZSE here.

SSEC SZSE

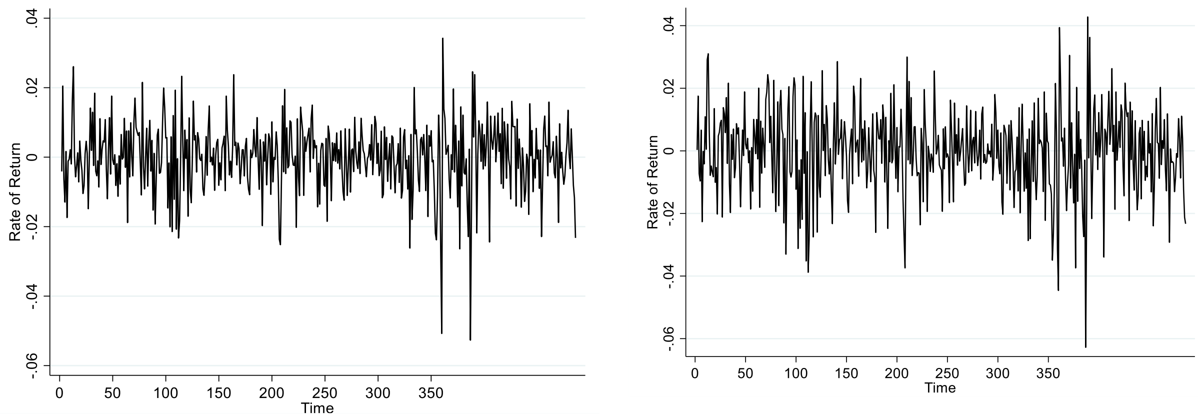


Figure 5. Yield

Photo credit: Original

In this part, the GARCH model is used to calculate the volatility of EI, which is put into the variance equation with the volatility of SSEC and SZSE measured by ARMA as the dependent variable. The spillover effect of the volatility of EI on the volatility of Chinese stock market is investigated.

As can be seen from the empirical results in Table 3, both ARCH and GARCH terms of the two models are significant, indicating that the return rates of the SSEC and SZSE have significant conditional heteroscedasticity, which can be used for GARCH modeling.

Table 3. ARMA-GARCHX estimation results

Variables	(1) SSEC			(2) SZSE		
	Coefficient	Std. err	p>|Z|	Coefficient	Std. err	p>|Z|
Mean equation						
AR, L28	0.3124	0.8770	0.722			
MA, L28	-0.2643	0.8888	0.766			
Constant	0.0000	0.0004	0.956	-0.0001	0.0005	0.840
Variance equation						
EURO, sigma-sq	30.4495	2.2937	0.000	29.7685	4.4814	0.000
GARCH (1, 1)						
ARCH, L1	0.0247	0.0135	0.067	0.0459	0.0186	0.014
GARCH, L1	0.9355	0.0183	0.000	0.9263	0.0240	0.000
Constant	-16.5310	0.4754	0.000	-16.1546	0.8690	0.000

4. Discussion

Much studies have been done to figure out how stock markets act with other monetary markets. Especially, the work of Gang Jin Wang, Chi Xie etc. in 2016 revealed that stock markets have great volatility spillovers to foreign exchange (FX) markets [5]. Comparably, the spillover effect of FX on stock market are studied in this article. Moreover, they point out that volatility spillovers vary with time, mainly caused by big financial events [5]. Accordingly, data in the past two years are chosen to study recent spillover effect for the sake of avoiding the influence of pandemic.

From the estimation results of external explanatory variables, the volatility of EI (for the convenience of coefficient explanation, this paper expands the volatility by 10000 times) increases by 1 unit, the volatility of SSEC increases by 30.4495 units, and the volatility of SZSE increases by 29.7685. The coefficients are all significant at 1% level.

The significant coefficients shows that the volatility spillovers of EI to Chinese stock markets do exist. The effect on SSEC is slightly bigger than that on SZSE, probably because the volume of Shanghai Stock Exchange is bigger, and there are more businesses between Europe and listed companies.

For investors, the result may be instructive. The volatility spillovers indicate that when investing in Chinese stocks, one should not only focus on domestic financial events. Events in Europe also matter.

5. Conclusion

First, this article collects data of EI, SSEC and SZSE from 2020-9-16 to 2022-9-16, finds that their log returns are stationary. Since basic qualitative analysis can’t tell whether the impact of Euro appreciation on Chinese stock markets is positive or not, VAR model is constructed to draw the impulse response diagram and cumulative effect diagram. Specifically, in the period of $s = 0$, if the euro return rate increased by 1 unit, the impact on the return rate of SSCE and SZSE will show positive and negative alternating results in the future, but both the size and frequency of the positive effect were larger than the negative effect. From cumulative effect diagram, the article finds that after 60 periods of cumulative impact, the net impact on the Shanghai stock market and Shenzhen stock market is about 7% and 6.5%, respectively. Finally, ARMA-GARCH model is built to measure volatility spillovers of EI on Chinese stock markets. The empirical result shows that this volatility spillovers do exist. To be specific, if the volatility of EI increases by 1 unit, the volatility of SSEC will increase by 30.4495 units, and the volatility of SZSE will increase by 29.7685. The spillover is greater on SSEC, probably because of the volume of Shanghai Stock Exchange is bigger, and there are more businesses between Europe and listed companies.

References

[1] Lee J W, Zhao T F. Dynamic relationship between stock prices and exchange rates: Evidence from Chinese stock markets[J]. Journal of Asian Finance, Economics and Business, 2014, 1(1): 5-14.

[2] Beh W L, Yew W K. Macroeconomic factors and stock markets interdependencies: Evidence from United States and China[J]. Journal of Critical Reviews, 2020, 7(5): 68-74.

[3] Chen H, Hu D. The Interaction between Interest Rates and Stock Returns: A Comparison between China and US[J]. 2015.

[4] Zhang J, Zhuang Y. Cross-market infection research on stock herding behavior based on DGC-MSV models and Bayesian network[J]. Complexity, 2021, 2021.

[5] Wang G J, Xie C, Jiang Z Q, et al. Who are the net senders and recipients of volatility spillovers in China's financial markets? [J]. Finance research letters, 2016, 18: 255-262.

[6] Sims C A. Macroeconomics and reality[J]. Econometrica: journal of the Econometric Society, 1980: 1-48.

[7] Makridakis S, Hibon M. ARMA models and the Box–Jenkins methodology[J]. Journal of forecasting, 1997, 16(3): 147-163.

[8] Engle R F. Statistical models for financial volatility[J]. Financial Analysts Journal, 1993, 49(1): 72-78.

[9] Saikkonen P, Lütkepohl H. Local power of likelihood ratio tests for the cointegrating rank of a VAR process[J]. Econometric Theory, 1999, 15(1): 50-78.

[10] Chang P L, Sakata S. Estimation of impulse response functions using long autoregression[J]. The Econometrics Journal, 2007, 10(2): 453-469.

[11] Anderson O D. Moving average processes[J]. Journal of the Royal Statistical Society: Series D (The Statistician), 1975, 24(4): 283-297.