

# International Capital Flows, Dynamic Changes in Cryptocurrency and Noble Metal Markets

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**Abstract.** In 2022, with the implementation of tightening monetary policies by FOMC, US dollar is experiencing a dramatic appreciation in a very short period. Though numerous studies have demonstrated the connection between the traditional currency market, cryptocurrency market, and precious metal market, rare studies are exploring the relationships between the three markets under a special political environment. This paper selects USDCNY exchange rate, gold and silver, and bitcoin as the representatives of three markets and then tests the volatility response of return on gold & silver and return on bitcoin to the change of return on USDCNY exchange rate. By employing impulse response function and ARMA-GARCHX model, the paper verifies the change of exchange rate will exacerbate the volatility of returns on gold & silver and bitcoin significantly, which suggests high risk and uncertainty of the cryptocurrency market and precious metal market in a complex and extreme political environment. Investors and speculators should take prudent investment strategies in such environment.

**Keywords:** Exchange Rate, Precious Metal, Bitcoin, Volatility, ARMA-GARCHX.

## 1. Introduction

Intending to suppress the price pressure generated from high inflation, the Federal Open Market Committee (FOMC) planned to take a series of aggressive monetary contractions, and thus FOMC announced to raise the interest rate at FOMC meetings and scheduled to implement this monetary policy in March, May, July, September, and November. Until the 28th, of July, FOMC has raised 25 basic points, 50 basic points, and 75 basis points in March, May, and June respectively. With the tightening monetary policies, predictably, the US dollar is experiencing a soaring appreciation. Since the Chinese Central Bank keeps the interest rate constant in 2022, this paper proposes to set CNY as a proxy to reflect the real-time value of USD. As shown in fig 1, the exchange rate of CNYUSD was maintained at around 6.34 before the first interest rise occurred in March. Corresponding with the interest rise, the exchange rate increased dramatically in March, April, and May, and then been stable in June, at around 6.72. With the skyrocketing appreciation of the dollar in such a short period, not just the commodity sector, but all the financial sectors are experiencing a huge shock, via various channels, for instance, price volatility, risk, and expectative return of financial assets might change greatly with a sudden appreciation of the dollar.



**Figure 1** the exchange rate between USD and CNY

Even Bretton Woods System has become a far-distance memory, the precious metals are still connected with USD closely, as the price of precious metals is normally bided by USD. Generally, precious metals, especially gold and silver, are recognized as both a kind of commodity and a special currency. From commodity aspect, gold and silver are scarce with great intrinsic value, which are also important industrial raw materials; from currency aspect, gold and silver have been perceived as a sample of wealth for thousands of years, which indicated they have the capacity of value storage and more they are used as mediums of exchange or quote of goods' value. Because of the bivariate attributes of precious metals, the USD price of gold and silver might be sensitive to the change in the USD exchange rate and various macroeconomic factors. Becher and Soenen discover the USD price of gold rise accompanied by the depreciation of USD relative to other foreign currencies, this relationship has also been verified by Sjasstad and Scacciavillani through a comparison of the USD price of gold with DM (Deutsche mark) price of gold when the exchange rate of USDDM decreased [1, 2]. Then, they uncover the volatility of gold prices generated from floating exchange rates among the major currencies mainly. However, Pukthuanthong, and Rol, by using the VAR model and Granger Causality Analysis, prove that the negative relationship between change in the gold price and the change of the value of bided currencies is trivial, while the volatility of USD price, JPY price, DM price, and GBP price are similar [3]. Otherwise, via the asymmetry-powered GARCH model, Tully and Lucey confirm that the dollar effective exchange rate is the most influential factor to impact the mean of return on gold, while the exchange rate falls to explain the variance and fluctuation of gold price [4]. However, interest rate cannot explain either mean or variance of the return on gold, demonstrating gold price has limited relation to the interest rate. Interestingly, the coefficient of 1-lagged autoregression conditional variance is significant at 1% level and has the largest absolute value among all the coefficients, implying the high volatility persistence of gold price. This result is identical to the finding of Hammoudeh and Yuan, who also verify the high volatility persistence of return on gold and silver [5]. But on the contrary, the impact of interest rate on gold and silver is significant and dampening, not just mean but variance, similar to the conclusion of Hashim et al. [6]. Consequently, the interest rate and USD exchange rate have an impact on gold and silver, both price and volatility, however, the strength of this impact is unstable, and might shift over time.

Bitcoin is firstly introduced by Nakamoto in 2008, to be designed as a new substitute for conventional currency. However, the nature of bitcoin still confused scholars and economists today because it is ambiguous and overlaps with various financial fields. In the article of Dyhrberg, she describes bitcoin as "the asset between gold and traditional currency", since bitcoin shares many similar attributes with gold [7]. Like gold, bitcoin is scarce as the total amount of bitcoins has been decided by the algorithm, but it lacks intrinsic value, at this point, bitcoin approaches more with conventional currency, like dollar. Additionally, bitcoin has some unique features from both gold and traditional currency, first, it is decentralized and has no related departures or organizations to monitor the market of bitcoin. Although decentralization endows the very high liquidity for bitcoin, the risk of bitcoin is also high because of the high possibility of fraud and manual manipulation; plus, the value or credit of bitcoin is not guaranteed by any legal regimes or blocs, which implies the value of bitcoin are utterly determined by the market, and thus this feature brings high instability and volatility of its price. Geuder et al. have demonstrated that cryptocurrencies are a kind of special speculative asset, as their price is associated with bubble behaviors significantly [8]. Baur et al. and Corber et al. respectively confirm that bitcoin is insolated and has limited connection with other financial assets, for example, gold and oil futures, which manifests bitcoin's failure to be a hedge asset but more suitable as risk diversification [9] [10]. The latest research from Kwon, via exploring the tail behaviors of bitcoin, gold, and dollar, illustrates the significant negative correlation between bitcoin and dollar while rejecting the similarity between bitcoin and gold, according to different tail features [11]. The conclusion may emphasize the currency and investment attribute of bitcoin. Consequently, the feature of bitcoin indicates it is a speculative asset mainly but not either a traditional currency or commodity, hence its price is highly uncertain and will be volatile with the fluctuation of other financial factors, such as interest rate and exchange rate.

With previous research, the general interactions between exchange market, precious metal market, and cryptocurrency market are clear, however, there is rare research to test the interaction between those three markets, within some unusual scenarios. As in a specific period, the interaction model and volatility relativity are quite different from normal time, for exchange rate, bitcoin, and gold. For both investors and policymakers, risk management is always important, therefore scholars must clarify the risk of assets in some unusual periods to avoid irrational investment or policy making. Whereby, the main purpose of this paper is to examine the risk sensitivity of returns on gold, silver, and bitcoin with the change of return on USDCNY exchange rate, within the monetary contraction period of 2022. By employing the impulse response function and ARMA-GARCH model, the author discovers that: the change of return on the USDCNY exchange rate has a significant impact on both means and volatility of return on gold, silver, and bitcoin. And the conclusion further manifests that investors shall be more prudent to invest financial assets in such period.

The rest of this paper is organized as follows: Part 2 is research design, including data sources, unit root test, and identification strategy; Part 3 reports empirical results; Part 4 is discussion and part 5 is conclusion.

## 2. Research Design

### 2.1 Data sources

As FOMC starts to implement tightening monetary policies in 2022, to avoid interference from previous period, this paper collects data from January 4th to July 28th with 137 observations for each variable, and the four selected variables are the logarithm of the daily closing price of gold, silver, bitcoin, and USDCNY exchange rate. Intending to ensure the continuance of time-series with exchange rate, the trading price of gold, silver, and bitcoin at weekends have been excluded from the sample.

### 2.2 Unit Root Tests

#### 2.2.1 ADF-test

When making a time-series examination, the necessary and sufficient condition of the test shall be that the sequence is time-series stationery. As if the sequence is nonstationary and drifts randomly, the sequence will fail to cluster at the expectation of the sequence, and the past information and innovation will interfere with the result permanently. Dicky D.A and Fuller W.A. propose a method to test the unit root process of sequence, also known as DF test, [12].

$$p_t = \phi_0 + \phi_1 p_{t-1} + \varepsilon_t \quad (1)$$

Equation (1) is a standard 1 lag autoregression model, the stationary condition is that the coefficient  $\phi_1 < 1$  Using ordinary least squares estimate, the coefficient  $\phi_1$  is:

$$\widehat{\phi}_1 = \frac{\sum_{t=1}^T p_{t-1} p_t}{\sum_{t=1}^T p_t^2}, \quad \widehat{\sigma}^2 = \frac{1}{T-1} \sum_{t=1}^T (p_t - \widehat{\phi}_1 p_{t-1})^2 \quad (2)$$

As  $P_0=0$ , and T is the sample quantity, then making DF-test:

$$DF = \frac{\widehat{\phi}_1 - 1}{SE(\widehat{\phi}_1)} = \frac{\sum_{t=1}^T p_{t-1} e_t}{\widehat{\sigma} \sqrt{\sum_{t=1}^T p_{t-1}^2}} \quad (3)$$

And hypothesis is  $H_0: \phi_1 = 1$ , and  $H_1: \phi_1 < 1$  when p-value is small enough to reject hypothesis null, that indicates there is no unit root in sequence. However, many sequences in finance and

economy cannot be described as random drafting processes and they are fitted with autoregressive integrated moving average model (ARIMA), therefore the formula of such sequence.

$$X_t = c_t + \beta X_{t-1} + \sum_{j=1}^{p-1} \phi_j \Delta X_{t-j} + e_t \quad (4)$$

$$\Delta X_t = X_t - X_{t-1}$$

Therefore, when  $\beta = 1$ , equation (4) is AR (p-1) model of  $\Delta X_t$

When  $\beta < 1$ , equation (4) is AR (p) model of  $X_t$

And then adjusted DF-test is:

$$ADF = \frac{\hat{\beta}-1}{SE(\hat{\beta})} \quad (5)$$

And hypothesis is:  $H_0: \beta = 1$ , and  $H_1: \beta < 1$  rejects null hypothesis when there is no unit root process.

### 2.2.1 Test results

Table 1 exhibits the result of ADF-test of samples and their first-order differences. The origin sample sequences fail to reject the null hypothesis of ADF-test and indicate that random drafting process is existing in those sequences, while the t-values of first-order differences are significant at 1% level and demonstrate the stationary of logarithm of assets' yield rate.

**Table 1** ADF test

Variables	t-statistic	p-value
Price		
Gold	-1.831	0.6895
Silver	-1.970	0.6174
BTC	-2.079	0.5579
Exchange rate	-1.804	0.7030
Yield		
Gold	-9.571	0.0000***
Silver	-8.317	0.0000***
BTC	-7.623	0.0000***
Exchange rate	-7.618	0.0000***

### 2.3 Identification strategy

As a variable could be influenced by not just other independent variables, but also the variables from past time, a autoregressive model could be built to describe this process:

$$X_t = \phi_0 + \sum_{j=1}^p \phi_j X_{t-j} + \varepsilon_t \quad (6)$$

And  $\phi_0$  is constant,  $\phi_j$  is j-lagged autoregressive coefficient, only decided by lagged order but not time t;  $\varepsilon_t$  is innovation of  $X_t$ , which is also white noisy with independent and identically distribution, usually obey {0,1} normal distribution.

But as the sequence is a weakly stationary process, the expectation of each  $X_t$  shall be all the same, therefore  $X_t$  could be perceived as result of both expectation and accumulation of innovations from past time. Generally, such a sequence could be described by Moving Average model (MA), and the formula of it is:

$$X_t = \theta_0 + \sum_{j=1}^p \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{7}$$

And  $\theta_0$  is expectation of variance X,  $\theta_j$  is the coefficient of j-lagged innovation,  $\varepsilon_{t-j}$  is the innovation of  $X_{t-j}$ , which is white noisy with independent and identical distribution, like  $\varepsilon_t$ .

When combining both AR(p) model and MA(q) model to describe sequence, the autoregressive moving average model (ARMA) is

$$X_t = \phi_0 + \sum_{j=1}^p \phi_j X_{t-j} + \sum_{l=1}^q \theta_l \varepsilon_{t-l} + \varepsilon_t \tag{8}$$

Set  $B$  is backshift, as  $B^j X_t = X_{t-j}$ , therefore ARMA (p,q) could be rewritten to be MA(q):

$$X_t - \sum_{j=1}^p \phi_j X_{t-j} = \phi_0 + \sum_{l=1}^q \theta_l \varepsilon_{t-l} + \varepsilon_t \tag{9}$$

$$\begin{aligned} (1 - \phi_1 B^1 - \phi_2 B^2 - \dots - \phi_p B^p) X_t &= X_t - \sum_{j=1}^p \phi_j X_{t-j} \\ (1 + \theta_1 B^1 + \theta_2 B^2 + \dots + \theta_q B^q) \varepsilon_t &= \sum_{l=1}^q \theta_l \varepsilon_{t-l} + \varepsilon_t \end{aligned} \tag{10}$$

$$\begin{aligned} \left(1 - \sum_{j=1}^p \phi_j B^j\right) X_t &= \phi_0 + \left(1 + \sum_{l=1}^q \theta_l B^l\right) \varepsilon_t \\ X_t &= \frac{\phi_0}{\left(1 - \sum_{j=1}^p \phi_j B^j\right)} + \frac{\left(1 + \sum_{l=1}^q \theta_l B^l\right)}{\left(1 - \sum_{j=1}^p \phi_j B^j\right)} \varepsilon_t \end{aligned} \tag{11}$$

$$X_t = \mu + \left(\sum_{j=0}^{\infty} \psi_j B^j\right) \varepsilon_t \tag{12}$$

And  $\psi_0 = 1$ , equation (12) is also known as Wold expression of ARMA (p, q), and  $\psi_j = \frac{\partial X_{t+l}}{\partial \varepsilon_t}$  is impulse response function of ARMA (p, q), it means to bring  $X_{t+l}$  an additional variable  $\psi_j$  when  $\varepsilon_t = 1$ .

When considering multiple vectors in AR(p) model, that is vector autoregressive model (VAR) and its formula is:

$$\begin{aligned} r_t &= \phi_0 + \Phi_1 r_{t-1} + \Phi_2 r_{t-2} + \dots + \Phi_p r_{t-p} + a_t \\ r_t &= \phi_0 + \sum_{j=1}^p \Phi_j r_{t-j} + a_t \end{aligned} \tag{13}$$

$$r_t = \begin{bmatrix} r_{1t} \\ r_{2t} \\ \vdots \\ r_{kt} \end{bmatrix}, r_{t-j} = \begin{bmatrix} r_{1,t-j} \\ r_{2,t-j} \\ \vdots \\ r_{k,t-j} \end{bmatrix}, \Phi_j = \begin{bmatrix} \phi_{11,t-j} & \phi_{12,t-j} & \dots & \phi_{1k,t-j} \\ \phi_{21,t-j} & \phi_{22,t-j} & \dots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{k1,t-j} & \dots & \dots & \phi_{kk,t-j} \end{bmatrix}, a_t = \begin{bmatrix} a_{1t} \\ a_{2t} \\ \vdots \\ a_{kt} \end{bmatrix} \tag{14}$$

And  $r_t$  is vector of k variables at time t,  $\Phi_j$  is j-lagged cross-correlation matrix between vector  $r_t$  and vector  $r_{t-j}$ , and single unit of it is  $\phi_{ab,t-j} = corr(r_{a,t}, r_{b,t-j})$ , when a=b, the cross correlative coefficient is j-lagged autoregressive coefficient of variable  $r_{a,t}$ ;  $\phi_0$  is a 1\*k constant matrix;  $a_t$  is innovation matrix

Similar to AR(p) model, the characteristic function of VAR(p) is:

$$I - \sum_{j=1}^p \Phi_j Z^j \tag{15}$$

Therefore, as VAR(p) is a stationary sequence, the cross-correlative matrix should cluster to the null matrix when  $j = \infty$ , the stability condition of VAR(p) is that:

First, transfer VAR(p) into VAR (1)

$$\hat{r}_t = \begin{bmatrix} r_t \\ r_{t-1} \\ \vdots \\ r_{t-p} \end{bmatrix}, \hat{a}_t = \begin{bmatrix} a_t \\ a_{t-1} \\ \vdots \\ a_{t-p} \end{bmatrix}, \Phi^* = \begin{bmatrix} \Phi_1 & \Phi_2 & \cdots & \Phi_{p-1} & \Phi_p \\ I & 0 & \cdots & 0 & 0 \\ 0 & I & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & I & 0 \end{bmatrix} \hat{r}_t = \Phi^* \hat{r}_{t-1} + \hat{b}_t \tag{16}$$

Establish the characteristic polynomial of equation (16).

$$\lambda I - \Phi^* \tag{17}$$

Calculate the solution of equation (17) when  $\det(\Phi^* - \lambda I) = 0$ , the VAR(p) model is stable if all the solutions are inside the unit circle.

Following equation (12) the Wold expression of ARMA (p, q), the Wold expression of VAR(p) is:

$$r_t = \mu + \sum_{j=0}^{\infty} \Psi_j a_{t-j} \tag{18}$$

And thus the  $\Psi_j$  is impulse response matrix of  $r_t$ .

Generally, in a typical AR process, shown in equation (6), the residual  $\varepsilon_t$  should be white noisy with independent and identical distribution, however, in financial research, some sequences have volatility clustering phenomenon, because the residual  $a_t$  is usually heteroskedastic and correlative with each other, despite they are nonlinear. Engle first develops introgressive conditional heteroskedasticity model (ARCH) and proposes to decompose the innovation  $a_t$  in to two parts: conditional standard variance  $\sigma_t$  and white noisy  $\varepsilon_t$ , while the conditional variance could be linearly expressed as [13]:

$$\begin{cases} a_t = \sigma_t \varepsilon_t \\ \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2 \end{cases} \tag{19}$$

$\alpha_0$  is constant of variance, and  $\alpha_m$  is the coefficient of past innovation, which means the extent of present volatility could be explained by past fluctuations.

However, in empirical work, conditional variance  $\sigma_t$  may need high lags to be described with ARCH model and that will bring a negative impact on model from two sides: 1. High lags need more parameters in model and it will reduce the simple's degree of freedom significantly, 2. Information penalty from a high degree of complexity. Bollerslev expends the ARCH to generalized ARCH (GARCH), considering autoregression of conditional variance itself. Interestingly, standard GARCH model has highly constructive similarity with ARMA model, as [14]:

$$\sigma_t^2 = \alpha_0 + \sum_{l=1}^m \alpha_l a_{t-l}^2 + \sum_{j=1}^s \beta_j \sigma_{t-j}^2 \tag{20}$$

The  $\beta_j$  is autoregressive coefficient of conditional variance.

Further, in order to explore the contribution of exogenous variables to the volatility of financial assets, GARCH model with additional distributed lag term (GARCHX) could be better than standard GARCH model, and formula of GARCHX is:

$$\sigma_t^2 = \alpha_0 + \sum_{l=1}^m \alpha_l a_{t-l}^2 + \sum_{j=1}^s \beta_j \sigma_{t-j}^2 + \sum_{i=1}^k \rho_i X_i \tag{21}$$

And  $X_i$  is exogenous which contributes volatility to variance, and  $\rho_i$  is the related coefficient of term  $X_i$ .

By combining ARMA model and GARCHX model, the joint model of ARMA-GARCHX is:

$$\begin{cases} Y_t = \phi_0 + \sum_{j=1}^p \phi_j Y_{t-j} + \sum_{l=1}^q \theta_l \varepsilon_{t-l} + a_t \\ a_t = \sigma_t \varepsilon_t \\ \sigma_t^2 = \alpha_0 + \sum_{l=1}^m \alpha_l a_{t-l}^2 + \sum_{j=1}^s \beta_j \sigma_{t-j}^2 + \sum_{i=1}^k \rho_i X_i \end{cases} \tag{22}$$

### 3. Empirical results

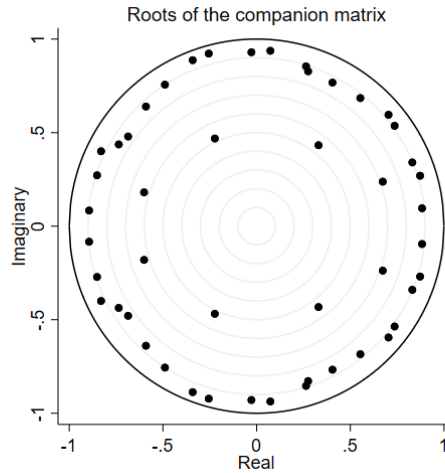
#### 3.1 VAR

For VAR order selection, the paper anticipates 12 lagged orders for the model and makes lags length test via STATA, and the results are shown in Table 2. For various information criteria, the test marks illustrate that 0 lag is the best option for the model, which implies the malfunction of information criteria to select an appropriate lag for the model. For likelihood-ratio statistic, lag-4, lag-7, lag-8, lag-9, lag-12 are all significant at 5% level, and the recommendation from varsoc confirms the lag-12 is the optimal selection for the model, hence, VAR (12) model will be built.

**Table 2** VAR model identification

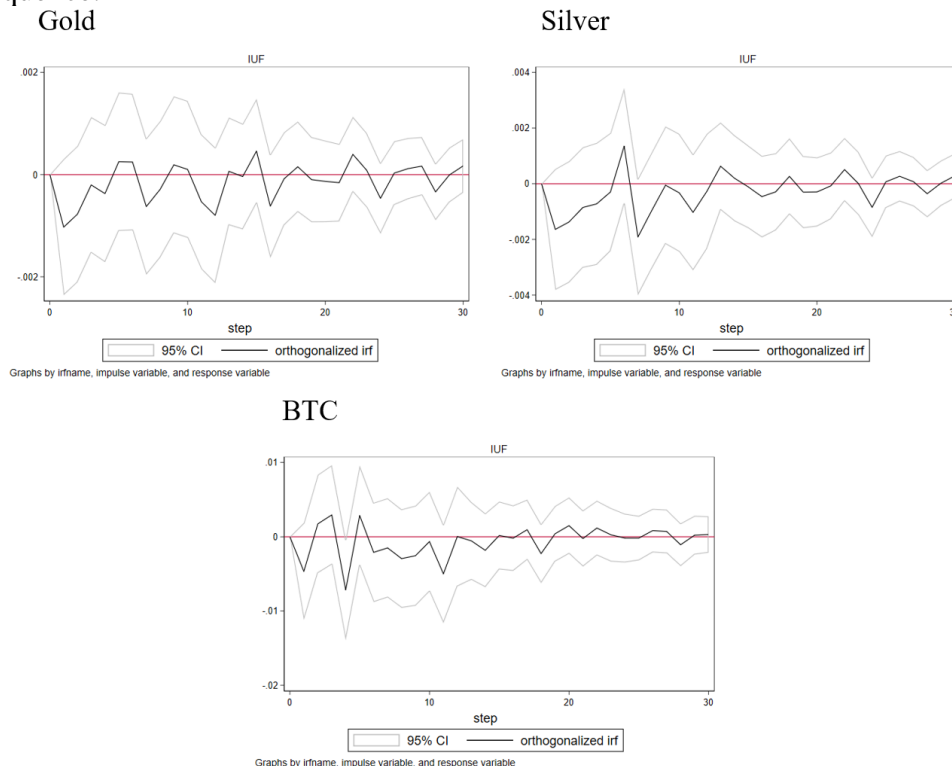
Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	1584.38				1.0e-16*	-25.49*	-	-25.399*
1	1588.99	9.2108	16	0.904	1.2e-16	-	-25.1214	-24.8513
2	1597.73	17.495	16	0.354	1.4e-16	-	-24.8566	-24.3705
3	1605.79	16.106	16	0.446	1.5e-16	-	-24.5806	-23.8784
4	1622.02	32.462	16	0.009	1.5e-16	-	-24.4365	-23.5182
5	1629.62	15.208	16	0.509	1.8e-16	-	-24.1533	-23.0189
6	1637.49	15.745	16	0.471	2.0e-16	-	-23.8744	-22.5239
7	1651.21	27.429	16	0.037	2.1e-16	-	-23.6897	-22.1231
8	1664.77	27.121	16	0.040	2.3e-16	-	-23.5025	-21.7199
9	1679.76	29.973	16	0.018	2.4e-16	-	-23.3383	-21.3396
10	1686.52	13.531	16	0.634	2.8e-16	-	-23.0416	-20.8268
11	1698.68	24.31	16	0.083	3.1e-16	-	-22.8317	-20.4008
12	1712.43	27.513*	16	0.036	3.4e-16	-	-22.6477	-20.0007

The solutions of characteristic polynomial of VAR (12) model have been illustrated in Figure 2. The visual results verify the roots of matrix inside the unit circle and thus manifesting the stability of VAR system.



**Figure 2** VAR stability

Setting return on gold, silver, and bitcoin as response variables and return on exchange rate as impulse variables, the results of IRF are shown in Figure 3. Obviously, with one unit change in exchange rate, the other variables all have visible oscillation to respond to the impulse, and maximum amplitude for bitcoin, gold, and silver are 0.6%, 0.1%, and 0.2% respectively. That shall be a reasonable result, whereby gold and silver are usually perceived as hedge assets and have resistance against shocks. On the contrary, as a speculative asset, bitcoin is more likely affected by a positive or negative shock, consistent with the research of Geuder et al. and Glaster et al. [8, 15]. The impact of impulse decays around 20 lags and vanishes gradually, fitting the basic feature of time-series clustering sequence.



**Figure 3** Impulse and response

### 3.2 ARMA-GARCHX estimation results

Before establishing ARMA-GARCHX model, it is essential to select the order for AR model and MA model. Calculating the autocorrelative function and partial auto-correlative function of returns on gold, silver, and bitcoin, the results are visualized in Figure 4, 5 lagged, 19 lagged and 35 lagged PACFs and 5 lagged ACF of bitcoin are significant at 5% level and reject to be white noisy; however, all the lagged PACFs and ACFs of gold are insignificant and cannot reject white noisy hypothesis; for silver, only 19 lagged PACF is significant, while all the ACFs of it are insignificant as well. Consequently, the possible ARMA models for bitcoin, silver, and gold are ARMA (5,5), AR (19), and ARMA (0,0), and more ARMA (0,0) is also a kind of white noisy. Noticeably, with empirical test, the AR (19) model is not effective to adapt the sequence of silver and the program fails to estimate specific coefficients of this model, so the sequence of return on silver also could be considered as a white noisy. For GARCH model, there is still no theoretical method to select the order of model appropriately, but according to the experience, GARCH (1,1) model is usually available and efficient, hence, anticipating the GARCH (1,1) model is reasonable to describe the volatility of the assets.

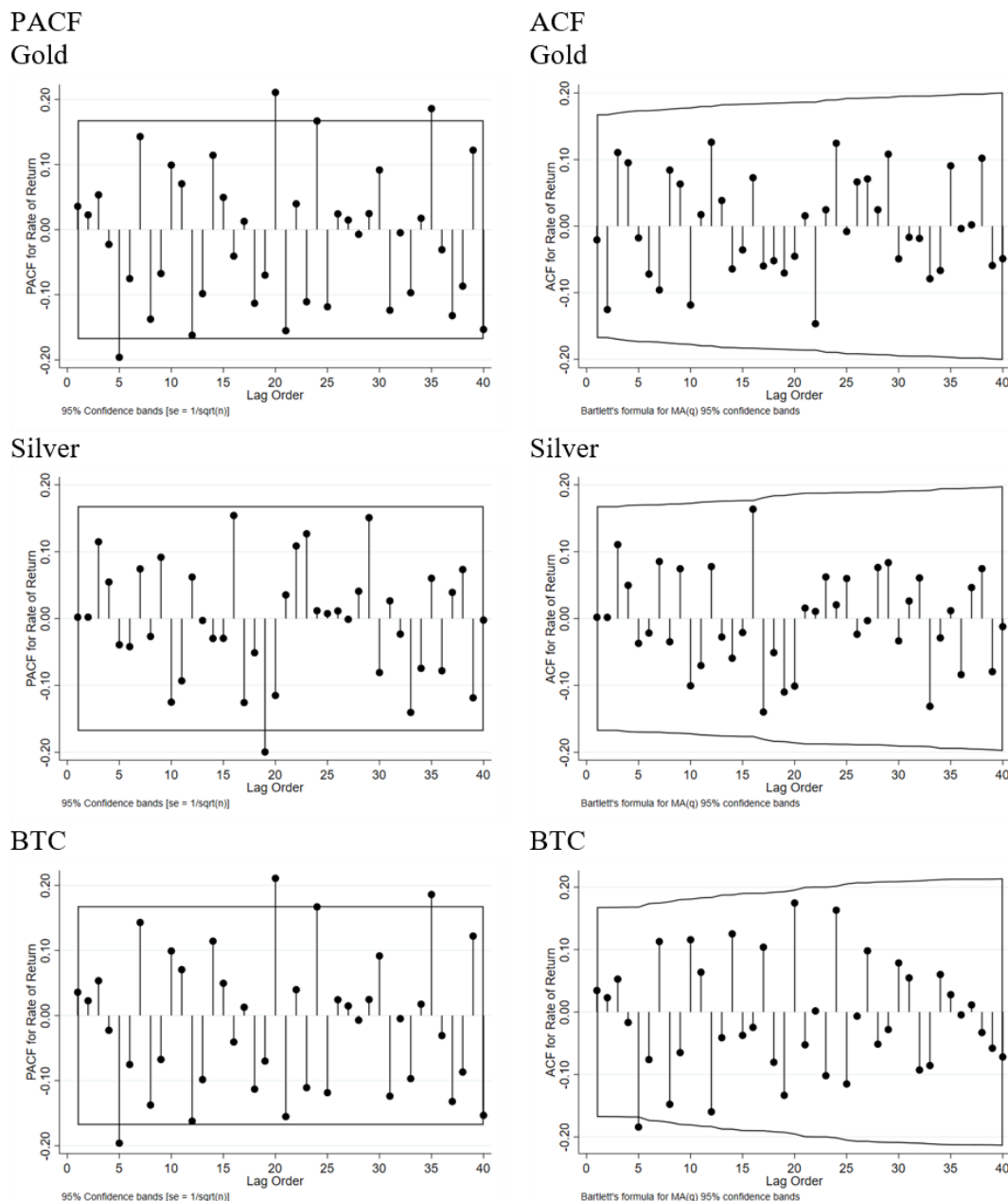


Figure 4 PACF and ACF

The results of ARMA-GARCHX model are exhibited in Table 3. Since at least one coefficient of ARCH and GARCH of each item are significant at 10% level, the effectiveness of ARMA-GARCHX model is verified. Surprisingly, the related coefficients of exchange rate for gold, silver and bitcoin are 155.18, 206.34, and 60.92, all significant at 5% level. This finding has not just meaningful in statistics, but more economic, as it demonstrates the gold, silver and bitcoin are quite sensitive to the value of dollar, in the environment with aggressive monetary policies.

**Table 3** ARMA-GARCH estimation results, variance equation

Variables	GOLD		AG		BTC	
	Coef.	Std. err	Coef.	Std. err	Coef.	Std. err
Exchange rate	155.1860**	78.8116	206.3454***	55.4349	60.9215***	20.8007
ARCH (-1)	0.1331*	0.0803	0.1536***	0.0517	0.0450	0.0560
GARCH (-1)	0.0047	0.2207	0.7392***	0.1513	0.5707***	0.1510
Constant	-9.6370***	0.3473	-9.5033	0.3680	-5.8147***	0.1786

#### 4. Conclusion

By employing VAR model and ARMA-GARCHX model, the paper successfully verifies that gold, silver, and bitcoin will be volatile fiercely, corresponding the change of exchange rate from two channels. First, the result from VAR model and impulse response function suggests that the change of exchange rate has a constant long-term influence on expectations of return on silver and gold, and bitcoin; then, via ARMA-GARCHX model, the change of exchange rate will exacerbate the volatility of return on gold & silver and bitcoin. The coefficients of exchange rate for gold, silver, and bitcoin are 155.18, 206.34, and 60.92, all significant at 5% level.

This fact might warn that the potential risk of the precious metal market and cryptocurrency market, which relate to conventional currency market, could raise magnificently when the monetary environment becomes complex and extreme. Exposed to the shock, investor shall apply more prudent investment strategies to avoid volatility and uncertainty.

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