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THE IMPACT OF THE TRADE-WAR BETWEEN THE USA AND CHINA ON THE VOLATILITY OF THE CHINESE YUAN AN ANALYSIS CONDUCTED USING THE GARCH (1, 1) MODEL

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Abstract:*This study investigates whether different specifications of univariate GARCH models can usefully forecast volatility in the foreign exchange market. The study uses only estimatesfrom a symmetric GARCH model, namely GARCH (1, 1) forCNY/USD exchange-rate. The dataset is obtained from "Investing.com" and covers the period between January 2016 to September 2019. The data focuses on the trade-war between USA and China due to a major political conflict. China economic growth was greatly reduced to levels not seen since 1992 while US economic forecasts have also decreased.This paper arrives at the conclusion that the GARCH (1, 1) model could be successfully used to better predict the volatility of the currencies than simply using unconditional volatility.*

JEL classification:O16, G1, G17

Key words: GARCH (1, 1), modelling volatility, exchange-rates, CNY/USD

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1. INTRODUCTION AND OBJECTIVES

Volatility is widely recognized as a measure of the dispersion of returns for a market index or security; the importance of volatility in current financial markets has been addressed by a large number of studies (Alexander, 2001).

Although the standard deviation has its limitations as a measure of risk, this approach is used most frequently to assess an investment`s risk (Emmer et al., 2013). The main disadvantage of making use of Standard Deviation to measure the risk is the absence of suitable weightings that occur at a specific time ascribed to the errors. In other words, the weightings of the errors that occur nearer the present time (t_0) have the same impact and significance as the weightings of errors arising at (t_n). Moreover, using Standard Deviation as a measure of risk provides little response on skewed datasets (Calvet and Fisher, 2008). The mean can be influenced substantially by outliers in the data, which would imply that the datasets are skewed. Therefore, Standard Deviation depends considerably on outliers from the datasets. Two phases are involved in the estimation of historical correlation and volatility: the unbiased estimates of unconditional variance which are based on weighted averages of squared returns and the conversion into volatility and correlation estimates.

The historic volatility is built on weighted average of squared returns. Therefore, most of the financial classical theories have to be based on the primary assumption of multivariate normal independent identically distributed (i.i.d) return distributions. Under the assumption of most financial classical theories, the volatility does not depend on time. Therefore, in case volatility does not remain constant over a period of time, all the changes attributed to estimations of volatility are considered white noise. Particularly, traditional models assume that the variance of errors is constant over a period of time. This process is known as homoscedasticity. However, according to an article published byWiley Online Library (2012), the variance of errors does not remain constant over a period of time which implies that the volatility depends on the time period in the majority of financial markets. This process is known as heteroscedasticity.

Most of the financial markets do not show shapes that are identically distributed. On the contrary, most of the financial markets indicate that volatility depends on the time period. Therefore, the development of the GARCH (General Autoregressive Conditional Heteroskedasticity) model in 1982 by Engle and the ARMA (Autoregressive Moving Average) model by Whittle in 1951were introduced to adjust for the issue presented above.

The Chinese Yuan has dramatically dropped to a record low in more than a decade provoking the US to label China a currency manipulator since the yuan was allowed to decrease below the landmark seven per dollar threshold. In general, Beijing has previously prevented its currency from sliding below this emblematic level. However, a brief month-long ceasefire between the US and China has abruptly broken down when the US President vowed to impose 10 percent tariffs on the remaining $300bn of Chinese imports. Therefore, The People's Bank of China allowed the Chinese Yuan to move freely and breach the seven per dollar level since the financial crisis in 2008. Usually, the yuan is not freely traded due to the government involvement that restricts its movement against the US dollar. (BBC Business, 2019)

A weaker yuan makes Chinese exports cheaper to buy with foreign currencies and more competitive. Therefore, consumers worldwide can purchase Chinese products more cheaply. On the other hand, a weaker yuan will also make imports into China more expensive. Such trend could drive up inflation and create worries in its already slowing economy.(Aljazeera, 2019)

According to Bloomberg (2019), global bond markets were directly affected with the UK and German yields dropping to fresh record lows after China required state companies to hold imports of US agricultural products.

This paper analyses the fluctuations of the CNY from January 2016 to September 2019in order to see the impact of the plans laid out by the future President of the United States of America, Donald Trump to counter the unfair trade practices from China.The study uses only forecasts from asymmetric GARCH model, namely theGARCH (1, 1) model introduced by Engle, for theCNY/USD exchange-rate pair.

2.METHODOLOGY AND DATA

This chapter aims to present the nature of GARCH models from both statistical and financial perspectives. The leverage effect and volatility clustering are both part of the GARCH framework by basically extending the linear regression model with another equation known as the conditional equation. This chapter presents theonly asymmetric GARCH model used to investigate characteristics of the volatility. The estimation using the maximum likelihood approach highlight the stability of the GARCH (1, 1) model, the choice of data period and the way it affects long-term volatility.

In a generalized autoregressive conditional heteroscedasticity (GARCH) model, returns are assumed to be generated by a stochastic process with volatility varying according to the time at which is measured. A GARCH model introduces more detailed assumptions about the conditional distributions instead of modelling the data after they have been collapsed into a single unconditional distribution. Since the conditional variance is an autoregressive process, these conditional distributions change over time in an auto-correlated manner.(Alexander, 2001)

As already mentioned in the introduction, this paper will make use of only symmetric GARCH, namely the GARCH (1, 1) model. A symmetric GARCH models means that a symmetric response of volatility to both negative and positive shocks will be illustrated when a shock occurs, while the asymmetric GARCH models allow for an asymmetric response showing that positive shocks will lead to lower volatility than negative shocks. There are different mathematical interpretations of the GARCH (1, 1) model and to facilitate the numerical estimation of these models, the version of Alexander (2001) presented below has been adopted.

The symmetric GARCH (1, 1) equation used within this research paper is presented below:

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2$$

$$\omega > 0;\ \alpha, \beta \geq 0$$

Where ω is the constant, α is the GARCH error coefficient, β is the GARCH lag coefficient and σ_t^2 is the conditional variance since any past information considered to be relevant is included in the one period ahead estimation of calculated variance. While the unconditional variance of GARCH model is constant and concerned with long-term behavior of time series, the conditional variance relies on the past information. The formula for unconditional variance of the GARCH (1, 1) model is presented below:

$$Var(u_t) = \frac{\omega}{1 - (\alpha_1 + \beta)}$$

The coefficient measures the degree to which today's volatility shock is encompassed within the volatility of the next period; in other words, it relates to the long-term volatility. The unconditional variance remains constant for as long as $\alpha_1 + \beta$ is strictly lower than 1.

According to Alexander (2001), GARCH models are frequently estimated on intraday and daily data in order to capture volatility clustering effects in the returns of financial assets as it disappears when returns are observed over long time periods. The estimation of GARCH parameters is done by maximizing the value of the log likelihood function using time varying mean and variance. Thus, maximizing the GARCH (1, 1) likelihood comes to solving the problem of maximizing:

$$\ln L(\theta) = -\frac{1}{2}\sum_{t=1}^{T}(\ln(\sigma_t^2) + (\frac{u_t}{\sigma_2})^2)$$

where the parameters of conditional variance equation are represented by θ.

Maximization of the log likelihood function for univariate GARCH models should encounter few convergence problems. Changes in the coefficient estimates will be induced by changes in the data. However, unless there are real structural breaks in the data generation process, the parameter estimates should not change majorly as new data arrive.

For the log likelihood function to be well defined, a certain minimum amount of data is necessary. Frequently, numerous years of daily data are needed to ensure proper convergence of the model. Thus, the data within this study covers the period from January 2016 to September 2019 resulting in a total of 978 daily observations.

3. EMPIRICAL RESULTS AND ANALYSIS

Autocorrelation is the early evidence to support the use of ARCH/GARCH models. Therefore, the Box-Pierce or the Q test was used to identify whether autocorrelation within the dataset exists (Alexander, 2001). The test is applied to the residuals of the time series after fitting an ARCH (p, q) model to the data. The formula used to identify autocorrelation is presented below:

$$Q = n \sum_{k=1}^{h} r_k^2$$

Where Q represents the Box-Pierce statistic, n represents the total number of observations, m is the number of parameters and h represents the maximum lag considered.

Generally, the Box-Pierce test is defined as:

H_0: Prices do not have any significant historic dependence

H_1: Prices do have significant historic dependence

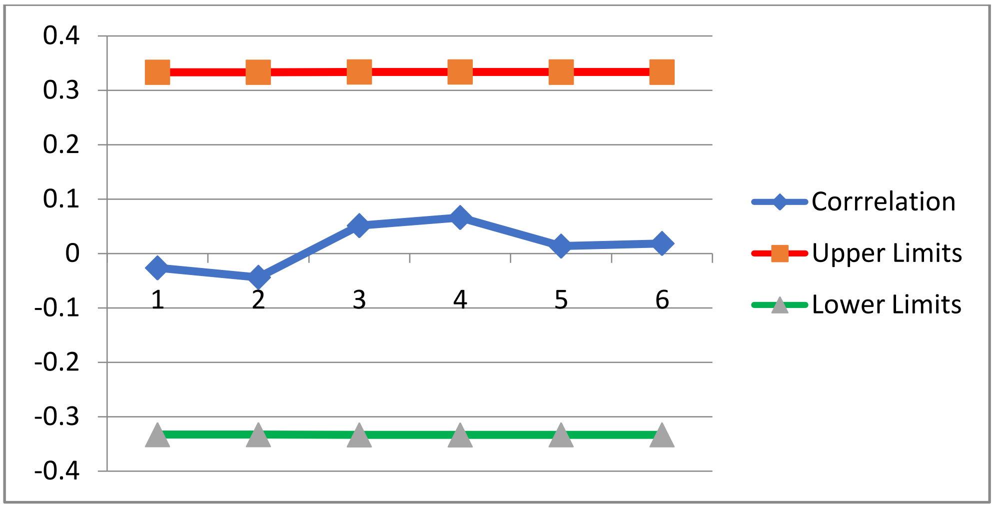

Fig 1. *CNY/USD Autocorrelation for the period January 2016 to September 2019 (elaborated by the authors)*

The figure 1 presented below shows that autocorrelation in returns does no exists for the CNY/USD exchange rate for the period January 2016 to September 2019Since the correlation line is between the upper limit and the lower limit, the existence of autocorrelation in returns does not exist. Furthermore, in order to be certain, the application of the Box-Pierce test or the Q test is also made.

Essentially, the Q test statistic shows that in case that residuals are white noise, the Q statistic follows a χ^2 distribution with (h-m) degrees of freedom. In case each r_k value is close to 0 then Q statistic is very small; otherwise, in case some r_k values are large then Q is relatively large. Then a comparison between the Q statistic with χ^2 distribution will be made.

Since six lags were plotted, this paper only focuses on the r_k^2 values for the first 6 observations. As a result, the full Q test process for the CNY/USD exchange-rate between June 2016 to September 2019 is presented below:

$$Q = 978 \sum_{k=1}^{6} r_k^2 = 8.6622$$

As a result, the Q statistic for the above mention period is compared with Chi-squared critical value of 12.6 for a 5% significance level. Thus, the Q statistic is lower than 12.5 for a 5%

significance level, leading to the conclusion that returns do not have significant historic dependence. Therefore, H_0 is the accepted hypothesis.

Table 1 presents how the likelihood function was calculated and how to maximize the log likelihood function using Excel Solver.

*Caption for the table*Table 1.

CNYUSD	GARCH (1,1)
Jan 2016 – Sep 2019	
w	0
a	0.0944
b	0.9055
a +b	1.00
q	-
g	-
l	-
LT Vol	N/A
LogLikelyhoodFunction	5307.4873

Note: $\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta\sigma_{t-1}^2$ – was used for parameter estimation

The parameter estimates for CNY/USD exchange-rate using the GARCH (1, 1) model between January 2016 to September 2019 are shown in Table 1. Note that the unconditional volatility that is estimated that is using an equally weighted average of all the squared return mean deviations differs markedly from the long-term volatility estimate given by the GARCH (1,1) model. There are few advantages of using the GARCH models discussed below compared to any other volatility models. Parameters within the GARCH models are optimally estimated using the maximum likelihood function. Furthermore, the persistence and reaction coefficients are estimated separately. Thus, a high persistence in volatility after a market shock is not automatically associated with a low reaction to market shocks. However,it can be identified from Table 1 that there is a high persistence in volatility since the trade-war period started and no reaction to this event.

Parameters within the GARCH (1, 1) model are optimally estimated using the maximum likelihood function. Furthermore, the persistence coefficientβshows a value that illustrates high persistence in volatility since the future President of the United States of Americalaid out plans to counter unfair trade practices from China in June 2016.

Any GARCH (1, 1) parameter estimate especially the estimate of the GARCH constant ($\widehat{\omega}$) are very sensitive to the historic dataset used for the model. In the case the sample covers approximately 2 years during which some extreme market movements were recorded due to tensions between the US and China, the estimate of the GARCH (1, 1) constant ($\widehat{\omega}$) is 0.In case this political argument between the two largest economies continues, a currency war might be triggered. There is a trade-off between having too much data and enough data for parameter estimates to be stable so that the long-term GARCH forecasts reflect as good as possible the current market condition but not exactly

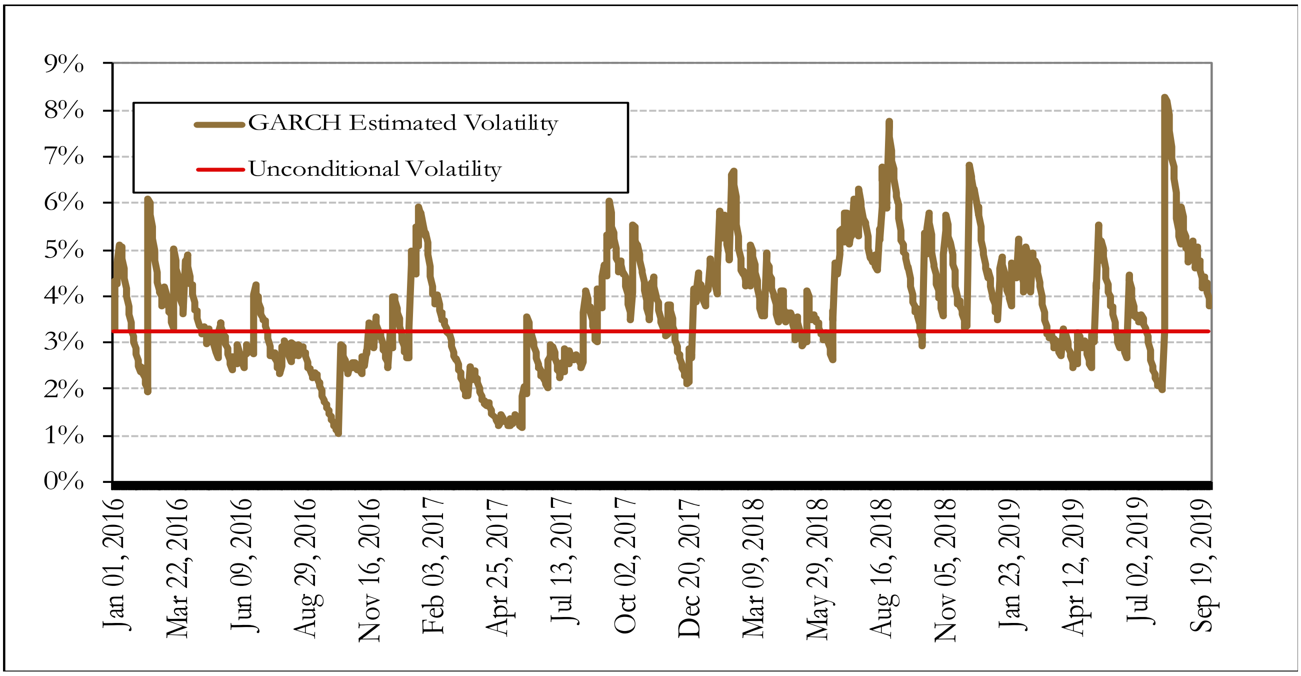

Fig 2. *Comparison between GARCH (1, 1) Estimated Volatility versus Unconditional Volatility for the CNY/USD exchange-rate from January 2016 to September 2019 (elaborated by the authors)*

Figure 2 presents that the i.i.d unconditional volatility estimate of 3.25% is approximately the same with the unconditional GARCH (1, 1) average volatility of 3.75%. However, it is not unusual to find differences between the i.i.d volatility and the long-term GARCH (1, 1)volatility since the GARCH (1, 1) model does not assume that returns are i.i.d. Figure 2 also illustrates that between June 2016 to September 2019, massive spikes in volatility of the

CNY/USD occurred after theplans revealed by the President of United States of America to counter unfair trade practices from China started.

As of 1st September 2019, China started imposing a 5% duty on US crude oil for the first time since the two largest economies in the world began their trade war for approximately two years ago. Furthermore, soybeans which were already subject to 25% tariffs increased with extra 5% tariff while the US began imposing 15% tariffs on $125 billion list of Chinese good including smart watches, Bluetooth headphones, footwear and an extra 10% on pork and beef. (Reuters, 2019)

4. CONCLUSION

The trade-war over tariffs between the US and China does not seem to be over very soon. The United States of America accused China of currency manipulation which is seen to float global trading rules by conferring unfair competitive advantage.However, China denied such allegations and imposed retaliatory tariffs in response to US actions. Since then, most of the major political events or decisions cause a dramatic rise in the volatility of the CNY. Our investigation arrives at the conclusion that the GARCH (1, 1) model could be successfully used to better predict the volatility of the currencies than simply using unconditional volatility.

CONFLICT OF INTEREST AND PLAGIARISM: The authors declare no conflict of interest and plagiarism.

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