ISSN:2790-1661 DOI: 10.56028/aemr.3.1.77

A Study of the Impact of Economic Policy Uncertainty in the US and China on the Volatility of the RMB Exchange Rate

Yuxin Cai [1, a]

[1] College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing, 211106, China;

[a] 17851308627@163.com

Abstract. This paper examines both theoretically and empirically how RMB exchange rate volatility will be affected by China and US economic policy uncertainty. It finds that RMB exchange rate volatility increases when economic policy uncertainty increases in China and the US; Besides, market uncertainty has a significant positive impact on RMB exchange rate volatility. The findings of this paper can provide useful references for financial regulation and forecasting the role of policy.

Keywords: Economic policy uncertainty; exchange rate volatility; market uncertainty.

1. Introduction

Policy makers are often neither accurate nor good at communicating future policy forecasts, with the result that government policy makers may create uncertainty in fiscal, regulatory, or monetary policy, being economic policy uncertainty [1].Uncertainty shocks can have important effects on the economy [2], and thus changes in economic policy uncertainty can have significant macroeconomic implications, and quantifying the effects of uncertainty shocks on key economic variables has been of great interest to policymakers.

Regarding the measurement of economic policy uncertainty, this paper mainly uses two indices, one is the news report-based Economic Policy Uncertainty Index (EPU) constructed by Baker et al. (2016) which is the most representative [3]. Secondly, Huang & Luk (2020) conducted text mining on 114 mainland Chinese newspapers to compile a series of novel indices of economic policy uncertainty in China [4].

There are two main questions in exploring the impact of economic policy uncertainty on RMB exchange rate volatility: first, whether economic policy uncertainty has a positive or negative impact on RMB exchange rate volatility, and second, how economic policy uncertainty affects RMB exchange rate volatility.

For the existing literature, foreign studies mainly focus on the relationship between the US dollar and other different national currencies. Krol (2014) finds that home country EPU and US EPU can increase exchange rate volatility for industrial and emerging economies [5]. Abid (2020) similarly focuses on exchange rate movements in emerging economies including Korea, India, Brazil, Mexico and Chile [6]. While domestic studies have mainly examined the relationship between the RMB and other major currencies or between China's exchange rate markets and those of other Asian countries. Thus, it is necessary to study the impact of China and the U.S. EPU on RMB exchange rate volatility.

The main contributions of this paper include the following two points. First, the paper uses the GARCH model to explore the impact of Sino-U.S. economic policy uncertainty on the RMB exchange rate over the period 2005-2020. The model estimates the impact of current day and lagged EPU values, as well as including the impact of non-policy uncertainty on exchange rate volatility, making the analysis more comprehensive. Second, most of the data used in the existing literature are monthly data, which may ignore important structural features of the sample data. If the natural period of the EPU is shorter than one month, using monthly data may not provide an accurate causal explanation and may even compromise the accuracy of the estimates. This paper uses daily data to explore the impact and more accurately reflect the dynamics of exchange rate volatility.

ISSN:2790-1661 DOI: 10.56028/aemr.3.1.77

2. Model Construction

In this paper, the following research framework is designed to explore the issue of the impact of economic policy uncertainty between the US and China on the volatility of the RMB exchange rate, drawing mainly on the GARCH model used by Bartsch (2019) [7].

First, exchange rate fluctuations are usually defined as

$$r_t = \ln(e_t) - \ln(e_{t-1}) \#(1)$$

where e_t refers to the current day's exchange rate and e_{t-1} refers to the previous day's exchange rate.

The classical GARCH model is as follows.

$$r_t = \alpha_0 + \beta_0 r_{t-1} + \varepsilon_t h_t^{\frac{1}{2}} \#(2)$$

$$h_t = \alpha_1 + \sum_{i=1}^{p} \delta_i h_{t-i} + \sum_{i=1}^{q} \varphi_i \varepsilon_{t-i}^2 \#(3)$$

Consistent with the efficient market assumption, the canonical GARCH (1, 1) model typically produces both a constant and an autoregressive coefficient in the mean equation that is close to 0. If the average daily exchange rate fluctuation is 0 and there are no significant autoregressive coefficients, α_0 and β_0 are both zero, then the variance is the only term left in the model.

Unlike the studies of Krol (2014) and Balcilar et al. (2016), Bartsch (2019) estimates the effect of both the current day EPU value and the lagged EPU value due to the timing of newspaper publication relative to the market opening times described above. $x_{i,t}$ contains the policy and non-policy uncertainty variables, both current day and lagged, so that the model is updated to the following form.

$$R_t = \varepsilon_t h_t^{\frac{1}{2}} \#(4)$$

$$h_t = \delta_1 h_{t-1} + \varphi_1 \varepsilon_{t-1}^2 + e^{(\alpha_2 + \sum \beta_i x_{i,t})} \#(5)$$

$$\sum \beta_i x_{i,t} = \sum_{j=1}^{n=2} \beta_j (\mathrm{Non-Policy-Uncertainty})_{t-j} + \sum_{k=0}^{n=1} \beta_j (\mathrm{EPU_{US}})_{t-k} + \sum_{k=0}^{n=1} \beta_j (\mathrm{EPU_{CN}})_{t-k} \#(6)$$

The current day EPU values are included in (6) as a reflection of the availability of newspaper information on that day. Non-policy uncertainty is taken as a lagged value to reflect the uncertainty of the latest release. An additional lagged value is added to each item to allow for immediate market adjustment.

3. Empirical Analysis

3.1 Descriptive statistics

Table 1 contains descriptive statistics for daily exchange rate fluctuations, U.S. EPU, China EPU, and market uncertainty. Since data on exchange rates are not available for weekends and holidays, and data on market uncertainty are not available for trading days when the NYSE is closed, the sample sizes for all four data sets are different. Based on the means and standard deviations, we can standardize these four data sets for subsequent analysis.

The results of the test are shown in the table below, the Ljung-Box statistic for daily exchange rate fluctuations Q=116.3408 has a p-value close to zero, thus indicating that it has a strong ARCH effect. Similarly, the Ljung-Box statistic of squared exchange rate fluctuations and the ARCH-LM test, both of which have p-values close to 0, results indicate the existence of ARCH effect.

ISSN:2790-1661 DOI: 10.56028/aemr.3.1.77

Table 1. Daily summary statistics

Variable	Exchange rate return	US EPU	CN EPU	MU
Obs	3835	5,582	5,582	3848
Mean		116.9455	132.1743	0
Std. Dev.	0.002	89.58388	68.2062	7.931317
Variance		8025.271	4652.086	62.90578
Skewness	0.2218195	2.536109	1.584071	2.048464
Kurtosis	19.60657	12.77708	8.758537	10.57275
Min	-0.02	3.32	0	-28.0045
Max	0.018	861.1	747.73	54.22493
Ljung-box（r=40）	116.3408 [0.0000]			
	Squared return			
Ljung-box（r=40）	350.1057 [0.0000]			
ARCH Lagrange multiplier（q=2）	12.054 [0.0024]			

3.2 Smoothness test

The standard method for checking the smoothness of the series is the unit root test, which will be analyzed in this paper using the ADF test and the PP test. Table 2 shows the results of the smoothness test with the p-value results of the ADF and PP tests in parentheses. The results show that σ^2, US EPU, CN EPU, MU all four data sets are smooth.

Table 2. P-value for tests of stationarity

Daily frequency	σ^2	US EPU	CN EPU	MU
Augmented Dickey-Fuller	[0.0002]	[0.0005]	[0.0002]	[0.0109]
60 Lags p-value				
Phillips-Perron	[0.0000]	[0.0000]	[0.0000]	[0.0000]
60 Lags p-value				

3.3 ARMA parameter estimation

The sequence can be determined to be a smooth non-white noise sequence by the previous sequence preprocessing, then the ARMA model can be used to model the sequence. First, the values of the sample autocorrelation coefficient (ACF) and the partial correlation coefficient (PACF) of the series are found, and then the ARMA (p, q) model of appropriate order is selected for fitting according to the nature of the sample autocorrelation coefficient and the partial autocorrelation coefficient, where p is the order of the autoregressive term and q is the order of the moving average term. The results of ARMA parameter estimation show that all series are best modeled as ARMA (1, 1) according to the AIC and BIC criteria.

Table 3. ARMA Selection

Daily frequency	
US EPU	（1，1）
CN EPU	（1，1）
MU	（1，1）
Squared Return	（1，1）

3.4 GARCH model estimation results

Based on the above series of operations such as smoothness test and parameter estimation, the model is determined as GARCH (1, 1). As can be seen from Table 4, the independent variables added in columns (2)-(4) are all insignificant and the coefficients on the variables are small or even converge to 0. Columns (5)-(7) are first-order differenced data, and only the Chinese EPU is

ISSN:2790-1661 DOI: 10.56028/aemr.3.1.77

significant at the 10% level in columns (5)(6), and market uncertainty and the US EPU lagged first order are significant at the 1% level in column (7), while the Chinese EPU is significant at the 5% level for both present value and lagged first order. The reason that the US EPU is insignificant most of the time may be because the US economy and regulators are large and diverse, the US EPU may not be significant, it may be that the US EPU has a faster intraday effect than the daily data, and finally it may be because the US monetary policy objectives do not include the exchange rate and therefore have a smaller degree of impact.

The reason for this may be because, on the one hand, the US, as a developed country, has stronger spillover of its EPU. On the other hand, uncertainty related to economic policy decisions, whether originating from potential fiscal or monetary policy decisions, discourages firms' investment activities. Not only because firms are uncertain about future aggregate demand, but also because it creates upward pressure. When EPUs rise in China and the US, investors tend to reduce their positions in risky assets and move their funds to relative safety. Better financial markets and greater currency liquidity in developed economies will lead to capital flows from China to the U.S., causing exchange rate volatility, so the U.S. EPU has a greater impact on RMB exchange rate volatility.In addition to this, the coefficient of MU is also significantly positive, proving that as market uncertainty increases, RMB exchange rate volatility also increases significantly. Numerically, the effect of MU on RMB exchange rate volatility is also greater than that of EPU, a result that is intuitive given the relative importance of policy and non-policy matters for day-to-day business activities.

Table 4. GARCH Model Results (2005.7.21—2020.10.30)

Variance	（1）	（2）	（3）	（4）	Δ（5）	Δ（6）	Δ（7）
ARCH	0.0234***	0.0231***	0.0234***	0.0253***	0.0231***	0.0232***	0.0254***
GARCH	0.978***	0.978***	0.977***	0.977***	0.978***	0.978***	0.977***
Constant	-0.0393***	-0.0384***	-0.0438***	-0.0438***	-0.0395***	-0.0395***	-0.0361***
L.Market uncertainty			0.0222	0.00252		-0.0119	0.114***
L2.Market uncertainty				0.0206			0.0172
US EPU		-0.0106	-0.00947	-0.00605	-0.00801	-0.00521	-0.0007
L.US EPU				0.00903			0.0850***
CN EPU		0.0137	0.00941	0.00966	0.0218*	0.0226*	0.0273**
L.CN EPU				-0.0199			0.0450**
Log likelihood	-4241.688	-4241.078	-4236.513	-4085.604	-4239.994	-4237.974	-4082.66
AIC	8491.375	8494.156	8487.026	8191.207	8491.989	8489.948	8185.321
BIC	8516.36	8531.633	8530.747	8253.664	8529.466	8533.669	8247.777

Conclusion

This paper uses the GARCH model to examine the impact of economic policy uncertainty in China and the U.S. on RMB exchange rate volatility, and obtains the following conclusions: first, when economic policy uncertainty in China and the U.S. increases, RMB exchange rate volatility

ISSN:2790-1661 DOI: 10.56028/aemr.3.1.77
also increases. Second, market uncertainty has a significant positive impact on RMB exchange rate volatility, and the degree of impact is greater than economic policy uncertainty in China and the US.

References

[1] Brogaard J, Detzel A. The asset-pricing implications of government economic policy uncertainty[J]. Management Science, 2015, 61(1): 3-18.
[2] Bloom N. The impact of uncertainty shocks[J]. Econometrica, 2009, 77(3): 623-685.
[3] Baker S R, Bloom N, Davis S J. Measuring economic policy uncertainty[J]. The quarterly journal of economics, 2016, 131(4): 1593-1636.
[4] Huang Y, Luk P. Measuring economic policy uncertainty in China[J]. China Economic Review, 2020, 59: 101367.
[5] Krol R. Economic policy uncertainty and exchange rate volatility[J]. International Finance, 2014, 17(2): 241-256.
[6] Abid A. Economic policy uncertainty and exchange rates in emerging markets: Short and long runs evidence[J]. Finance Research Letters, 2020, 37: 101378.
[7] Bartsch Z. Economic policy uncertainty and dollar-pound exchange rate return volatility[J]. Journal of International Money and Finance, 2019, 98: 102067.