Explaining the nature of economic volatility based on GDP and international trade: a study on China and the United States.

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2020

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Abstract

Economic volatility refers to the dispersion of an economic variable, especially the output growth, from its expected value, which has an immense impact on the livelihoods of many people and thus, regarded as one of the most important research topics of economic discourse. Gross domestic product (GDP) and international trade are two key indicators of a nation's economy that measure total economic activity and activities across borders, respectively. Hence to explain the economic volatility, this study aims to investigate its nature in terms of GDP and international trade of the two largest economy of world, China and the United States, from 1993 to 2018 using different ARCH-type models (GARCH, EGARCH and TGARCH). According to the findings, the TGARCH and EGARCH exhibit the best statistical fit and the asymmetric parameters of the models are significant for almost all the variables. Therefore, this study establishes that economic volatility in terms of real GDP growth and international trade (export and import) is asymmetric.

Keywords: Economic volatility, China, USA, GARCH, EGARCH, TGARCH.

JEL Classification: E32; E37

1. Introduction

Economic volatility, which is a complex and multidimensional phenomenon, can be the major obstacle to growth. Thus, there are ample reasons to study economic volatility to explain and monitor its nature persistently. Here, we take “volatility” as a generic variable, and tried to explain it in terms of GDP growth and international trade. Several previous studies investigate the volatility of GDP and conclude debated results, for example Hamori (2000) explore the volatility in GDP growth rates for United States, United Kingdom, and Japan, using ARCH type models and find that the volatility is not asymmetric. Ho and Tsui (2003) re-visits conditional volatility in real GDP growth rates of Japan, the United Kingdom, the United States and Canada using the same approach with some modifications and confirm that there is significant asymmetric volatility in the real GDP growth rates of the United States and Canada. Again Fountas et al. (2004) investigate the association between output variability and growth for Japan using quarterly data for the period of 1961–2000. They also find no evidence of asymmetry between output variability and growth, which is consistent with the findings of Hamori (2000). Moreover, exploring the asymmetry of trade and investigation focusing on China, the fastest growing economy is still scant.

Therefore to fulfill the gap, along with the widely addressed variables regarding economic volatility, the real GDP growth, export and import are also considered in this study, to represent the external and internal cause of economic volatility, respectively. In some research international trade is considered as the exogenous sources of macroeconomic volatility. For example, Van der Ploeg and Poelhekke (2009) and Di Giovanni and Levchenko (2010) have analyzed the effects of exposure to external shocks and examine macroeconomic volatility in terms of the standard deviation of exports, growth rates of terms of trade and Per Capita GDP. In addition, Cariolle (2012) has presented an extensive literature to explain the principles of measuring economic volatility and used the export revenue data for 134 countries.

Following the established literature, Autoregressive Conditional-Heteroskedasticity (ARCH) models are used to empirically investigate the economic volatility of China and the United States. From the family of ARCH models, Generalized Autoregressive Conditional-Heteroskedasticity (GARCH) model is frequently used to analyze the growth volatility of GDP. Although neither the ARCH nor the GARCH models can capture the commonly held phenomenon that volatility is likely to intensify when growth starts to decline and likely to subside when growth starts to rise (Engle and Ng, 1993), which is called asymmetric volatility; however, the "Threshold GARCH" (TGARCH) model introduced by Glosten et al. (1994) and Zakoian (1994) and the "Exponential GARCH" (EGARCH) model introduced by Nelson (1991) are able to explain the presence of asymmetric volatility. Moreover, for detecting the volatility movements, most of the previous studies presume a robust GARCH or "exponential GARCH" (EGARCH) method. Therefore, we choose these methods for our analysis.

The prime research objective of this study is to explore whether the economic volatility of China and the United States support asymmetry or symmetry by applying the principles of the ARCH-type models. Along with the econometric implications and explanation of the nature of economic volatility, this paper is also interesting from the viewpoint of data used in it. Since the US and China are two of the world largest economies and as far our concern no other research is found on these economies together hence this paper will definitely contribute to minimize this research gap of the related field.

The remainder of this paper is organized as follows: Section 2 discusses the data and methodology, which explains different models used in the analysis, section 3 presents the results and discussion, and section 4 concludes.

2. Data and methods

2.1. Models

The ARCH is a method that usually used to estimate and predict the change in variance in a time series data, where, in every case the variation of the explanatory variable is estimated depending upon the past values of it. The model ARCH (p) can be stated as follows:

$$y_t = \pi_0 + \sum_{i=1}^{k} \pi_i y_{t-i} + \varepsilon_t \tag{1}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 \tag{2}$$

The mean of growth rate is presented in equation (1) and an ARCH (p) model in equation (2), where the (p) refers to the ARCH terms. In equation 2, σ_t^2 denote the conditional variance of the error term (ε_t). which clearly specify that the conditional variance nothing but the weighted average of the square of the past residuals.

The GARCH model, originally developed by Bollerslev (1986) and advanced by Bollerslev et al. (1992, 1994), is mainly an extension of the ARCH model. The GARCH (p, q) model, where, p represents the ARCH terms and q refers to the GARCH terms, states that the variation depends on prior volatilities as well as on the past variances of the explanatory variable. The model GARCH (p, q) can be stated as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 \tag{3}$$

The three issue, specifically, the constant, the past information about the volatility (square of the past residual) and past predicted variance is used to define today's variance. This specification seems rational because the agent forecast present variance by using a constant variance, which is predicted from the past, or by using a weighted average of a long-term average. A simple GARCH (1, 1) model can be written as follows:

$$\sigma_t^2 = \frac{\omega}{1-\beta} + \alpha \sum_{i=1}^{\infty} \beta^{i-1} \varepsilon_{t-i}^2 \tag{4}$$

The GARCH variance is very similar to the variance of an ordinary sample. The only difference is that it put emphasis on the latest data by assigning declining weights to each of the past square value rather than an equal weight. It is called a conditional variance because σ_t^2 is a one-period predicted variance dependent on past data. The surprise in squared returns is specified by $v_{t=}\varepsilon_t^2 - \sigma_t^2$, which cannot be forecasted on the basis of the past information.

$$\varepsilon_t^2 = \omega + (\alpha + \beta)\varepsilon_{t-1}^2 + v_t - \beta v_{t-1} \tag{5}$$

Though this process has extreme heteroskedasticity, it can be seen immediately that squared errors follow an ARMA (1, 1) process. The autoregressive root, which governs the persistence of volatility shocks, is the summation of α plus β.

Until now, the effect of variance is considered as symmetric. However, it is also seen that downward changes in the market are accompanied by greater volatility than upward movements of the same size. TGARCH and EGARCH models analyze this asymmetry in variance. The TGARCH Model was developed by Zakoian (1994) and Glosten et al. (1994) independently. The model can be written as the following equation:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma D_{t-1}\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{6}$$

where, $D_t = 1$ for $\varepsilon_t < 0$, otherwise $D_t = 0$. This TGARCH specification allows the impact of the first lag of the squared residuals to have different effect upon volatility depending upon its sign. Good news ($\varepsilon_{t-1} > 0$) has an impact of α while bad news ($\varepsilon_{t-1} < 0$) has an impact of $\alpha+\gamma$. If γ term is significant, then there is existence of asymmetry, negative shock having a greater impact upon volatility if $\gamma > 0$ whereas, positive shock having a greater impact upon volatility if $\gamma < 0$.

EGARCH model which is developed by Nelson (1991), is an alternative to the TGARCH model and thus, can be used to test the robustness of our results. The specification for the variance is given in equation (7).

$$\log(\sigma_t^2) = \omega + \delta_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| + \delta_2 \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \beta \log(\sigma_{t-1}^2) \tag{7}$$

In EGARCH model, similar to TGARCH model if δ_2 is significant, it has asymmetry. However, there is no possibility of a negative variance because of the log transformation. The impact of the most recent residual is now exponential rather than quadratic. Good news ($\varepsilon_{t-1} > 0$) has an effect of .. $\delta_1 + \delta_2/\sqrt{\sigma_{t-1}^2}$ whereas the bad news ($\varepsilon_{t-1} < 0$) has an effect of $\delta_1 - \delta_2/\sqrt{\sigma_{t-1}^2}$. Therefore, a negative and significant δ_2 indicates confirmation of asymmetry, with a negative shock having greater impact on volatility. β represents the persistence of shocks to the conditional variance. We estimate each model by applying maximum likelihood procedure using EViews software.

2.2. Data

To achieve the stated objective, quarterly data of real GDP and trade (export and import) are collected from EIU CountryData database of Bureau van Dijk. The two largest economies, United States and China are considered in this study. The sample period, from the first quarter of 1993 to last quarter of 2018, is chosen because the data of our intended variables are available for this period only. Prior to the analysis, each variable is seasonally adjusted using moving average method and the quarterly growth rate is estimated to ensure the stationarity of each of the variables by using the following formula:

$$y_t = \frac{Y_t - Y_{t-1}}{Y_{t-1}} \times 100 \tag{8}$$

3. Result and discussion:

Table 1. Descriptive Statistics

	EXPCH	EXPUS	IMPCH	IMPUS	GDPUS	GDPCH
Mean	21.88	296.465	19.222	495.898	2165.737	1136.586
Median	122.4	434	151.9	615.8	2382	1927
Maximum	8424.5	2049	9215.7	3545.5	5915	27185
Minimum	-7534.2	-5088	-9056	-9275.5	-8475	-34331
Std. Dev.	2349.768	1004.79	2332.951	1740.856	2083.076	10835.93
Skewness	0.128	-2.408	-0.388	-3.364	-1.7	-0.666
Kurtosis	6.35	13.116	9.138	20.209	9.264	3.947
Jarque-Bera	46.566	517.82	157.874	1408.404	209.49	11.027
Probability	0	0	0	0	0	0.004
Sum Sq. Dev.	5.41E+08	98941081	5.33E+08	2.97E+08	4.25E+08	1.15E+10
Observations	99	99	99	99	99	99

Table 1 shows summary statistics on GDP, Export and Import of each country. EXPCH, IMPCH, and GDPCH represents the export, import and GDP growth rate of China whereas EXPUS, IMPUS, and GDPUS represents the export, import and GDP growth rate of the United States. The mean value of all variable is higher for United States whereas the standard deviation of all variables is larger for China. Jarque-Bera value is far from zero for all variables which means the data are not normal. The kurtosis value is greater than 3.0 for all variables. This suggests a traditional leptokurtic distribution, where the growth and trade data are more centered around the mean, with thicker tails compare to normal distribution.

Table 2 shows the pair wise unconditional correlation among variables. All the variables are positively correlated and highest correlation is found between import and export of United States.

Table 2. Correlation Matrix

	EXPCH	EXPUS	IMPCH	IMPUS	GDPUS	GDPCH
EXPCH	1					
EXPUS	0.539	1				
IMPCH	0.704	0.589	1			
IMPUS	0.523	0.866	0.558	1		
GDPUS	0.398	0.493	0.258	0.507	1	
GDPCH	0.179	0.281	0.210	0.198	0.272	1

Figure 1 in the panel explains describe the behavior of the real GDP growth rate, Import rate and Export rate for China and United States. These graphs indicate that all these growth rates have volatility and the graphs of china show greater volatility compare to the United States'.

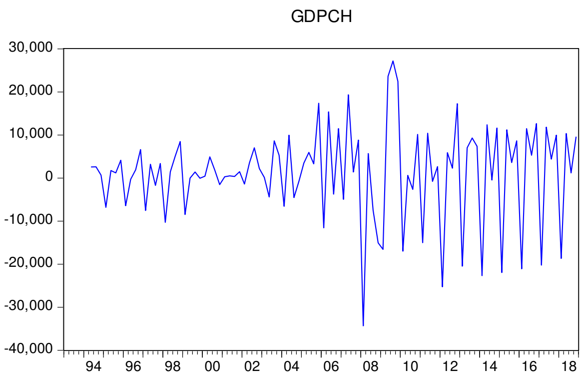

Figure1.1 GDP growth rate of China

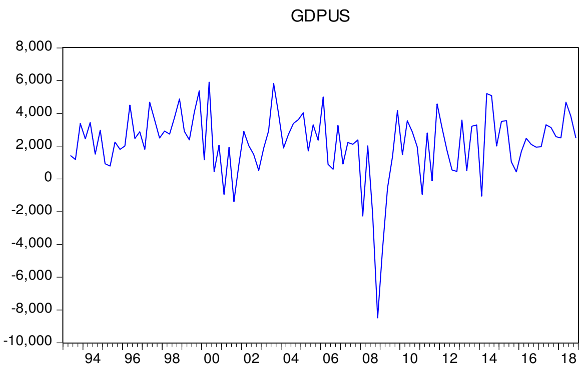

Figure1.2GDP growth rate of the US

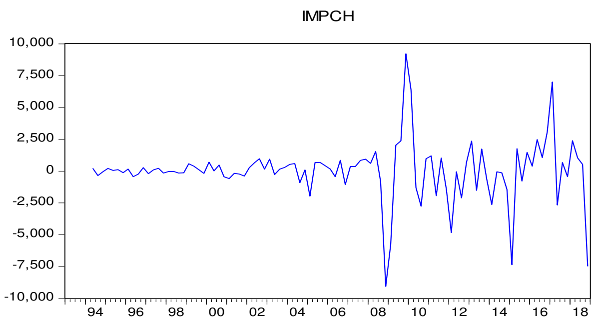

Figure1.3 Import of China

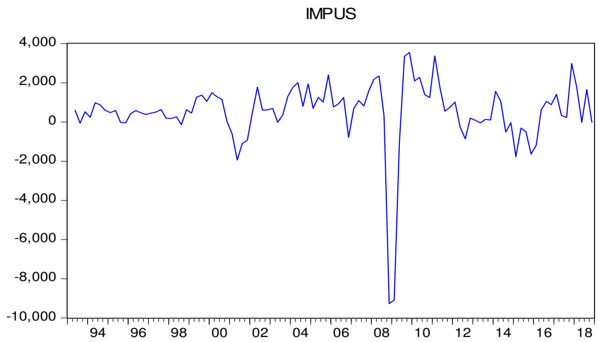

Figure1.4 Import of the US

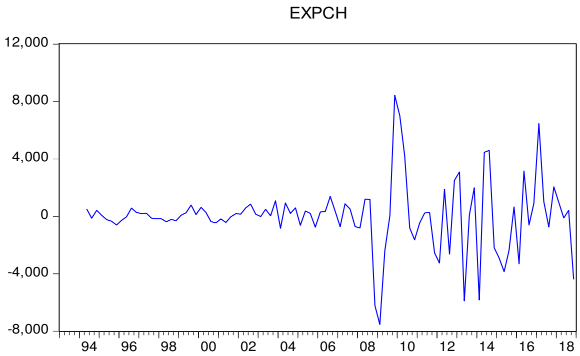

Figure1.5Export of China

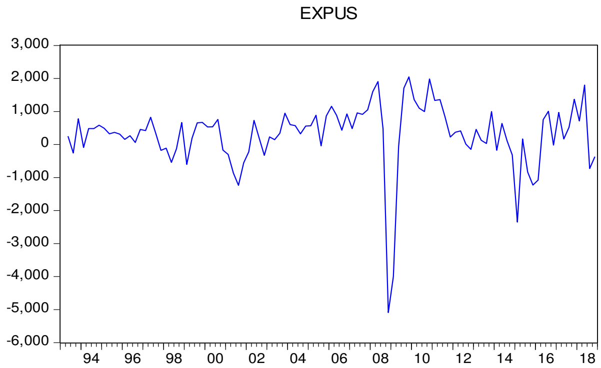

Figure1.6Export of the US

Figure1. Panel of growth rate of variables

As the reliability of the estimated parameters depends on the stationarity of the data, therefore, Augmented Dickey and Fuller (ADF) unit-root test (1979, 1981) is applied to confirm the stationarity of the data of GDP growth rate and trade. The regression for the unit-root test is conducted with a constant term; with a constant term and a time trend; and without any deterministic term. Here the ADF test is conducted by automatic selection of lag period. The results in table-3 show no existence of unit root as null hypothesis of having a unit-root is rejected at 1% level of significance in every case.

Table 3. Unit root tests of variables

	CHINA			UNITED STATES		
	GDP	Export	Import	GDP	Export	Import
Case 1	-4.341	-7.580	-7.00	-6.970	-6.335	-7.408
Case 2	-4.374	-7.630	-7.056	-6.981	-6.373	-7.440
Case 3	-3.642	-7.674	-7.101	-2.662	-5.909	-6.940

The results of the GARCH (1,1) model is presented in table 4. The conditional mean and conditional variance are stated in the as following equations:

$$\text{Mean equation,} y_t = \pi_0 + \sum_{i=1}^{k} \pi_i y_{t-i} + \varepsilon_t \text{ , for } k = 1 \quad (9)$$

$$\text{Variance equation, } \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 \quad (10)$$

In the mean equation, the lag order of the AR part is set to one, which is a quarter of a year according to our data. The results indicate ARCH term (α) of every variable except GDP of China and GARCH term (β) of only Chinese import are significant. The sum of α and β are 0.550, 0.573, 1.077, 0.646, 1.724 and 1.280 for Chinese and United States' GDP, import and export respectively. This is (α+β) called autoregressive root that represent the persistence capacity of volatility shocks. Therefore the result implies United States has better persistence to volatility shocks compare to China.

Table 4. Empirical results of GARCH model

Variable	GDPCH	EXPCH	IMPCH	GDPUS	EXPUS	IMPUS
π_0	6.120	-326.214	198.110*	2409.597***	583.106***	958.334***
	(6.613)	(390.05)	(104.398)	(256.119)	(108.903)	(239.793)
π_1	-0.349***	0.171	-0.227**	0.271*	0.604***	0.694***
	(0.099)	(0.131)	(0.105)	(0.150)	(0.060)	(0.094)
Variance Equation						
ω	6564.459***	3586939***	-19911	1301089*	119484.5***	465599**
	(1472.413)	(688671.9)	(28697.28)	(786011)	(33172.07)	(161851)
α	0.646	0.675*	0.159***	0.297**	1.715***	1.181***
	(0.269)	(0.376)	(0.047)	(0.122)	(0.376)	(0.249)
β	-0.097	-0.102	0.918***	0.349	0.009	0.099
	(0.119)	(0.078)	(0.021)	(0.308)	(0.08)	(0.120)
α+β	0.549575	0.573	1.077	0.646	1.724	1.280
Akaike info criterion	12.073	18.161	17.974	17.908	16.018	16.971
Schwarz criterion	12.205	18.293	18.103	18.036	16.147	17.099
Hannan-Quinn criter.	12.126	18.215	18.026	17.960	16.070	17.023

Robust Standard errors in parentheses. We use Bollerslev and Wooldridge (1992) robust standard errors. ***$p < 0.01$,

**p < 0.05,*p < 0.1.

The results of the T-GARCH model is presented in table 5. The following equation (11) and (12) present the conditional mean part and conditional variance part, respectively:

$$\text{Mean equation, } y_t = \pi_0 + \sum_{i=1}^{k} \pi_i y_{t-i} + \varepsilon_t \text{ , for } k = 1 \quad (11)$$

$$\text{Variance equation, } \sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma D_{t-1}\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (12)$$

The asymmetry term (γ) is significant for all variables of United States as well as for China except in case of Chinese export. Which indicates the existence of asymmetry that implies positive shock has a greater impact on volatility if $\gamma < 0$, whereas negative shock has a greater impact on volatility if $\gamma > 0$. Moreover, the term is negative for China and positive for United States which indicates the positive shocks has greater impact on volatility for china whereas negative shocks has greater impact on volatility for United States.

Table 5. Empirical results of TGARCH model

Variable	GDPCH	EXPCH	IMPCH	GDPUS	EXPUS	IMPUS
π_0	11.872	-283.703	281.832**	2264.589***	411.012**	348.385
	(7.419)	(389.959)	(97.456)	(233.677)	(139.779)	(228.268)
π_1	-0.365***	0.170	-0.193**	0.218	0.610***	0.564***
	(0.109)	(0.143)	(0.089)	(0.140)	(0.062)	(0.044)
Variance Equation						
ω	4954.641***	3585514***	-3907.067	1505501**	142728***	495021.8***
	(1434.506)	(830236)	(16340.31)	(760744)	(39305.96)	(90813.41)
α	1.623**	0.854	0.230***	-0.023	0.577	-0.084**
	(0.8)	(0.555)	(0.07)	(0.141)	(0.359)	(0.028)
γ	-1.537*	-0.329	-0.256**	0.565*	2.230***	3.257***
	(0.803)	(0.804)	(0.087)	(0.295)	(0.883)	(0.494)
β	-0.005	-0.082	0.972***	0.301	0.002	0.146**
	(0.163)	(0.093)	(0.022)	(0.282)	(0.07)	(0.065)
α+β	1.618	0.772	1.202	0.278	0.579	0.062
Akaike info criterion	11.983	18.178	17.869	17.874	15.975	16.786
Schwarz criterion	12.141	18.337	18.023	18.029	16.129	16.941
Hannan-Quinn criter.	12.047	18.242	17.932	17.937	16.037	16.849

Robust Standard errors in parentheses. We use Bollerslev and Wooldridge (1992) robust standard errors. ***p < 0.01, **p < 0.05,*p < 0.1.

Interestingly the persistence capacity measures (α+β) of China has became better compare to United States after considering asymmetry term by applying TGARCH model. In addition, the reported Akaike info criterion, Schwarz criterion and Hannan-Quinn criterion in table 5 are slightly lower in this model compare to GARCH model. Table-6 shows the results of the EGARCH model. The conditional mean part and conditional variance part are as follows:

$$\text{Mean equation,} y_t = \pi_0 + \sum_{i=1}^{k} \pi_i y_{t-i} + \varepsilon_t \text{ , for } k = 1 \qquad \text{eq-(13)}$$

$$\text{Variance equation, } \log(\sigma_t^2) = \omega + \delta_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| + \delta_2 \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \beta \log(\sigma_{t-1}^2) \qquad \text{eq-(14)}$$

Table 6. Empirical results of EGARCH model

Variable	GDPCH	EXPCH	IMPCH	GDPUS	EXPUS	IMPUS
π_0	9.312*	13.797	318.066***	2266.369***	275.00	194.518
	(5.038)	(98.924)	(114.306)	(247.731)	(187.414)	(311.869)
π_1	-0.287***	0.163	-0.208***	0.210*	0.684***	0.725***
	(0.118)	(0.135)	(0.069)	(0.125)	(0.063)	(0.058)
Variance Equation						
ω	0.066	-0.081	0.361	7.691*	6.555***	3.414***
	(0.200)	(0.350)	(0.299)	(4.382)	(2.025)	(1.162)
δ_1	0.270**	0.573***	-0.056	0.229	1.378***	0.680***
	(0.131)	(0.166)	(0.090)	(0.171)	(0.228)	(0.193)
δ_2	0.180**	0.043	0.237***	-0.411***	-0.528***	-0.744***
	(0.093)	(0.102)	(0.059)	(0.170)	(0.168)	(0.103)
β	0.970***	0.980***	0.980***	0.473	0.423***	0.721***
	(0.023)	(0.021)	(0.016)	(0.292)	(0.162)	(0.085)
Akaike info criterion	11.802	17.271	17.858	17.886	16.033	16.711
Schwarz criterion	11.960	17.429	18.012	18.040	16.187	16.865
Hannan-Quinn criter.	11.866	17.335	17.920	17.948	16.095	16.773

Robust Standard errors in parentheses. We use Bollerslev and Wooldridge (1992) robust standard errors. ***p < 0.01, **p < 0.05,*p < 0.1.

The result indicate that the asymmetry term (δ_2) is not zero and significant for all the variables of both of the countries except Chinese export and the values are negative for all variables of United States, therefore, the EGARCH is also showing the evidence of asymmetry. In addition, persistence capacity measures (β) of China are better compare to United States, which is consistent with the findings of TGARCH model. All three criterions of model performance measures are lower than GARCH model.

After analyzing the data using GARCH, TGARCH and EGARCH model, an evidence of asymmetry is identified as for almost all variables the asymmetry term is significant and the TGARCH and EGARCH model have better fit compare to the GARCH model according to the all three criteria of model performance.

4. **Conclusion**

The main purpose of this paper is to investigate the volatility of growth rate of Real GDP, and international trade (Export and Import) of two giant economies, China and United States to explain empirically whether it is symmetric or asymmetric. Particularly, this study make an attempt to test the hypothesis that the volatility would be less when the growth rate is increasing and would be more when it is declining. To achieve this quarterly data of variables for a period of from 1993 to 2018 analyzed using GARCH, TGARCH and EGARCH model in terms of the significance testing of parameters and the overall goodness of fit of the model selection criterion. The GARCH model does not allow for parameter testing of asymmetry. However, both TGARCH and EGARCH model have asymmetric term. The empirical results show that the TGARCH and EGARCH model have better fit compare to the GARCH model according to the all three criteria of model performance. Moreover for almost all variables the asymmetry term is significant in TGARCH and EGARCH model.

Therefore, there is asymmetry between volatility and growth rates of selected macroeconomic variables of the countries studied.

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