Economics Bulletin

Volume 36, Issue 3

Bitcoin: a beginning of a new phase?

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Abstract

Although financial experts have often criticized Bitcoin for being too volatile as an asset and an independent electronic currency, the volatility of Bitcoin has declined at a rapid pace since January 2015. This study addresses if Bitcoin enters a new phase. Many extensions of GARCH have been carried out to adequately estimate Bitcoin price dynamics. Our results suggest that despite maintaining a moderate volatility, Bitcoin remains typically reactive to negative rather than positive news. Bitcoin market is still, therefore, far from being mature.

The authors are indebted to the anonymous referee for his/her thorough reading of the paper and thoughtful comments. Remaining shortcomings are the responsibility of the authors.
Citation: Jamal Bouoiyour and Refk Selmi, (2016) "Bitcoin: a beginning of a new phase?", *Economics Bulletin*, Volume 36, Issue 3, pages 1430-1440
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Submitted: May 08, 2016. **Published:** August 03, 2016.

1. Introduction

Created in 2009, the Bitcoin is a relatively new phenomenon. It is a peer-to-peer network that allows the transfer of ownership without the need of a third party. Bitcoin is regarded as the best-known digital currency to date. Although some consider Bitcoin to be a major financial innovation in recent years (Kristoufek 2013, Ciaian et al. 2014, Bouoiyour et al. 2015), others suggest that the excessive volatility observed in this market is a major concern (Yermack 2014, Bouoiyour and Selmi 2015). Since its birth, experts, traders and regulators have always criticized the viability of Bitcoin as an independent currency due to its excessive volatility. It is evident that when the price of a Bitcoin skyrocketed from some pennies in 2009 to nearly $1200 in 2013, people will need to be more cautious about serving Bitcoin as their day-to-day purchases. However, since January 2015, Bitcoin has consistently maintained a less pronounced volatility rate. Because of this decline in Bitcoin price variability, a growing number of traders and investors are purchasing Bitcoin as a major part of their investment portfolio. Beyond integrating or not Bitcoin into asset allocations, the main question we pose in this study: *Is this a beginning of a mature Bitcoin market?* To this end, we estimate the volatility of Bitcoin price for two main periods: the first period that spans between December 01, 2010 and December 31, 2014, and the second period spanning from January 01, 2015 to July 22, 2016.

Given the complexity of Bitcoin market, modeling the temporal dependencies in the conditional variance of Bitcoin price can be useful to capture the striking feature that Bitcoin moves more rapidly during some periods than others. For this purpose, it will be important to search a parsimonious technique enables to detect the hidden factors driving this virtual currency. Conditional heteroskedastic models are the basic econometric tools used to estimate volatility. Though these models have been proved to account for volatility clustering and leptokurtosis, they fail to model the nonlinear and leverage effects. To address these problems, we use a wide range of varying variance models to properly measure the volatility of Bitcoin price.

The remainder of the article proceeds as follows: Section 2 discusses the methodology and provides a brief overview of the data. Section 3 reports the main empirical results. The last section offers some concluding remarks.

2. Methodology and data

Volatility clustering and leptokurtosis are commonly observed in financial time series. Other phenomena usually encountered are the so- called “leverage effect” and “nonlinear effect”. The GARCH (General Autoregressive Conditional Heteroskedasticity)-type modeling has been and continuous to be very valuable tool in financial economics since the seminal paper of Engle (1982). Engle (1982) proposed to model time-varying conditional variance with Auto-Regressive Conditional Heteroskedasticity (ARCH) processes using lagged disturbances. He argued that a high ARCH order is required to properly capture the dynamic behaviour of conditional variance. The Generalized ARCH (GARCH) model of Bollerslev (1986) fulfills this requirement as it is based on an infinite ARCH specification which minimizes the number of estimated parameters, denoted as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (1)$$

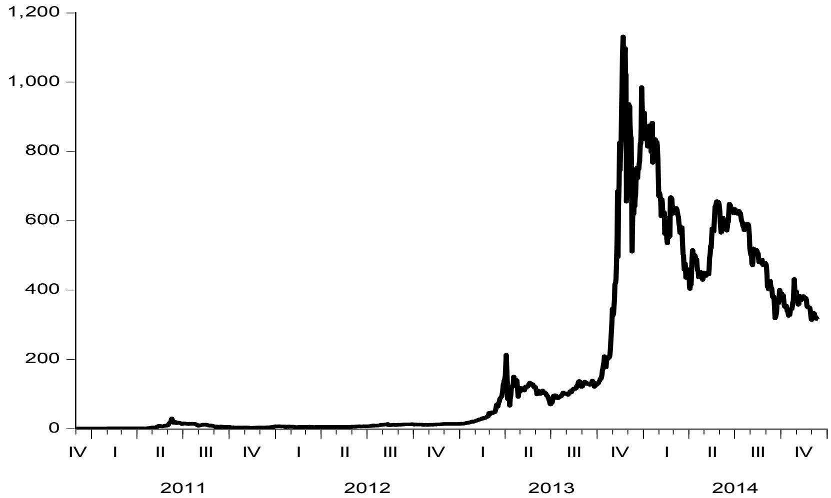
where α_i, β_i and ω are the parameters to estimate.

Even though the ARCH and GARCH models detect volatility clustering and leptokurtosis, their distributions are symmetric and linear. In other words, they do not account for possible asymmetry and nonlinearity in the volatility dynamics. To address these problems, we apply several GARCH extensions, such as the Exponential GARCH (EGARCH) model by Nelson (1991), the Asymmetric Power ARCH (APARCH) model by Ding et al (1993), the weighted GARCH model by Bauwens and Storti (2008) and the so-called Component with multiple thresholds-GARCH by Bouoiyour and Selmi (2014). Table A.1. (Appendices) reviews succinctly the different GARCH models employed in this study. Since no single measure of volatility has dominated the existing empirical literature, the appropriate model able to properly depict the volatile behavior of Bitcoin price can be selected using standard criteria such as the Akaike information criterion (AIC), the Bayesian (BIC) and Hannan-Quinn information criteria (HQ). These criteria are sufficient to judge the quality of conditional variance estimation in terms in terms of trade-off between goodness of fit and model parsimony.

For empirical purpose, we use daily data related to Bitcoin (BPI) over the period from December 01, 2010 to July 22, 2016. These data were derived from Blockchain (https://blockchain.info/). BPI is transformed by taking natural logarithms to correct for potential heteroskedasticity. Figure 1 clearly indicates that, since its birth, Bitcoin experienced several jumps and swings. Since January 2015, Bitcoin price has gradually gotten much less volatile than the previous years. After a period of sizable volatility especially during 2013-2014 (having been less than \$20 in January 2013, and reaching \$1,100 in January 2014, Figure 1, Period 1), the Bitcoin price becomes less turbulent since January 2015 (Figure 1, Period 2). A single Bitcoin was valued at around \$220.38 and does not exceed \$ 687.57 over the period from January 01, 2015 to July 20, 2016. This spotlights the beginning of new phase.

Figure 1. Bitcoin price evolution

Period 1: from December 01, 2010 to December 31, 2014



Period 2: from January 01, 2015 to July 20, 2016

Source: Blockchain (https://blockchain.info/).

3. Results

3.1. Bitcoin price volatility during turbulent period from December 01, 2010 to December 31, 2014

To choose the best model, we employed standard historical evaluation criteria (Akaike, Bayesian and Hannan-Quinn criteria). These criteria evaluate the models based on the history of volatility. Whatever the criterion used, the optimal model chosen is the Component with multiple Threshold (CMT)-GARCH model (Table A.2, Appendices). In most widely used GARCH models the conditional variance is defined as a linear function of lagged conditional variances and squared past returns. Though these models have been proved to be adequate for capturing the dependence structure in conditional variances, they contain important limitations, one of which is that they fail to detect structural breaks that may stem in the volatility process. The CMT-GARCH performed by Bouoiyour and Selmi (2014) accommodates multiple threshold orders[1], the weight between high and low volatility, and the leverage effect. Also, this model allows disentangling the process of volatility into a long-run time varying trend and short-run deviations from trend. This model is denoted as:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta(\omega + (\alpha + \gamma I_{(\varepsilon_{t-2} \succ 0)})\varepsilon_{t-2}^2 + \beta\sigma_{t-2}^2) \qquad (1)$$

where α_i, β_j, ω and γ are the parameters to estimate.

The estimates are reported in Table 1. Using CMT-GARCH, we find that the leverage effect is positive and significant, highlighting that bad news have greater impact on the conditional volatility. The persistence of conditional volatility ($\alpha + \beta + 0.5\gamma$) amounts 1.31. It tends towards an "explosive" process. Besides, we note that the sum of α and β is highly important (1.15), implying the existence of volatility clustering. The leverage effect is positive and statistically significant implying that the conditional variance reacts to bad news rather than good news. In addition, the alpha coefficient measuring the dependence of current period volatility on the past period disturbance seems significantly positive and stronger. Indeed, a large part of today's Bitcoin price volatility can be explained by past disturbances.

Table 1. Bitcoin volatility' parameters via CMT-GARCH model for the period from December 2010 to December 2014

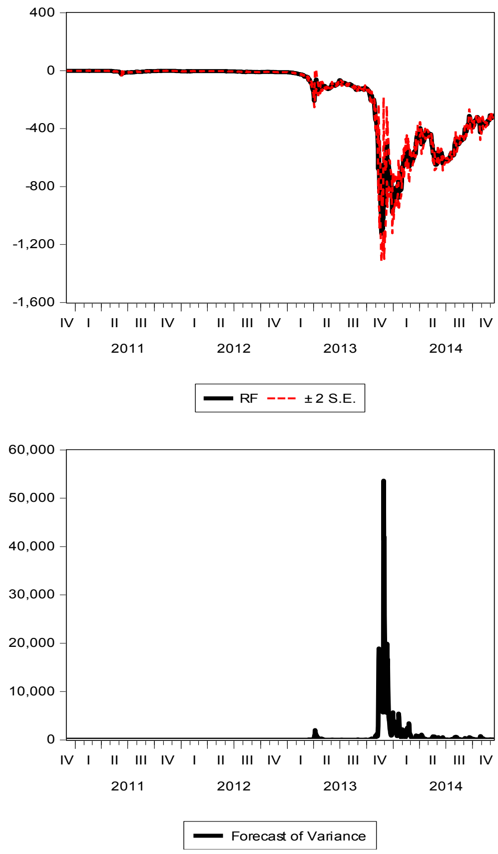
Dependent variable: (r_t)	
Mean Equation	
C	-0.008* (0.023)
r_{t-1}	-0.482*** (0.000)
Variance Equation	
ω	0.018 (0.146)
α	0.945*** (0.000)
β	0.2183 (0.134)
γ	0.3215** (0.006)
The duration of persistence: $\alpha + \beta + 0,5\gamma$	1.31
The leverage effect: γ	0.32

Notes: ω : The reaction of conditional variance; α : ARCH effect; β : GARCH effect; γ : Leverage effect; r_t: is the return of Bitcoin price; r_{t-1}: is the lagged Bitcoin price return; (.): the p-value; p-value<0.01: ***; p-value<0.05: **; p-value<0.1:*.

[1] This econometric technique allows describing the regime shifts (nonlinearity) in the volatility dynamics (Wu 2010).

It is well depicted from Figure 2 that the Bitcoin price evolves markedly over time. While it seems very low over the period 2011 to September 2013, it raises substantially from October 2013 before pursuing ups and downs since December 2013.

Figure 2. The conditional variance of Bitcoin price during the period from December 01, 2010 to December 31, 2014



Forecast: r F	
Actual: r	
Forecast sample: 12/01/2010 12/31/2014	
Adjusted sample: 12/02/2010 12/13/2014	
Included observations: 1472	
Root Mean Squared Error	20.08858
Mean Absolute Error	6.351196
Mean Abs. Percent Error	4.066927
Theil Inequality Coefficient	0.032663
Bias Proportion	0.000108
Variance Proportion	0.000001
Covariance Proportion	0.999892

3.2. Bitcoin volatility for the period from January 01, 2015 to July 20, 2016

Based on the same information criteria used above, we find that the optimal model enables to effectively assess Bitcoin price volatility for the period from January to June 2015 is the Asymmetric- power GARCH. One of the most important limitations of standard GARCH models is that they seem unable to capture the stylized fact that conditional variance tends to be heavier after a decrease in return than after an increase. To control for this leverage effect (or asymmetry) many alternative models have been proposed including the Asymmetric-power GARCH or (A-PARCH) developed by Ding et al. (1993). This GARCH specification controls for both asymmetry and nonlinearity in the process of volatility. It is expressed as follows:

$$\sigma_t^{\varphi} = \omega + \sum_{i=1}^{q} \alpha_i (|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i})^{\varphi} + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^{\varphi} \tag{2}$$

where α_i, β_j, ω and γ are the parameters to estimate.

Table 2 displays the Bitcoin price volatility parameters during the period that spans between January 01, 2015 and July 20, 2016. The volatility appears persistent but far from tending towards long memory process since $\alpha+\beta+0{,}5\gamma=0.65$ (far from 1). The asymmetrical effect is positive and statistically significant implying that the effect of bad news on the conditional variance exceeds that of good news. Indeed, the degree of asymmetry ($\frac{\alpha+\gamma}{\alpha}$) which measures the relative influence of bad news on volatility seems important (it amounts 0.41).

Summing up, by comparing the evolution of Bitcoin over the two considered periods, we note that the leverage effect remains positive and significant (even though the coefficient seems weaker, i.e., 0.208 for the second period against 0.321 for the first period), indicating that Bitcoin price is still typically more responsive to bad news. However, the duration of volatility's persistence from January 01, 2015 to July 20, 2016 ($\alpha+\beta+0{,}5\gamma=0.65$) becomes much less intense than that of the period from December 01, 2010 to December 31, 2014 ($\alpha+\beta+0{,}5\gamma=1.31$).

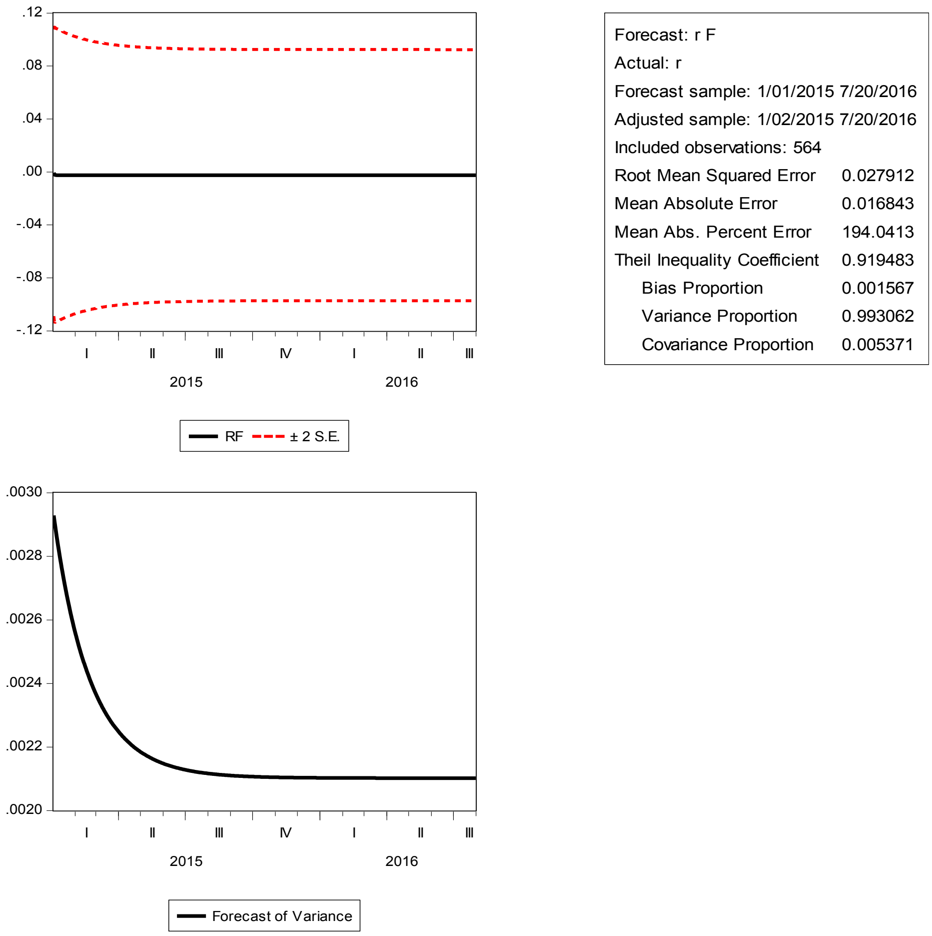
Table 2. Bitcoin volatility' parameters via A-PARCH model for the period from January 01, 2015 to July 20, 2016

Dependent variable: (r_t)	
Mean Equation	
C	0.098*** (0.000)
r_{t-1}	0.134* (0.069)
Variance Equation	
ω	0.675* (0.009)
α	-0.341* (0.023)
β	0.888* (0.0267)
γ	0.208** (0.006)
Duration of persistence: $\alpha+\beta+0{,}5\gamma$	0.65
Leverage effect: γ	0.20

Notes: ω : The reaction of conditional variance; α : ARCH effect; β : GARCH effect; γ : Leverage effect; ; r_t: is the return of Bitcoin price; r_{t-1}: is the lagged Bitcoin price return; (.): the p-value; p-value<0.01: ***; p-value<0.05: **; p-value<0.1:*.

By comparing Figures 2 and 3, we confirm the more volatile and persistent behavior of Bitcoin price over the period prior to January 2015. We clearly chow that the volatility of Bitcoin takes no large time to smooth over the period spanning from January 2015 to July 2016. Also, we note that the standard deviation becomes more important for the second period; hence the volatility process is likely to be less precise.

Figure 3. The conditional variance of Bitcoin price during the period from January 01, 2015 to July 20, 2016



4. Conclusions

Bitcoin price volatility seems to be a major concern for most of the general public at this time. The good news for the Bitcoin community is that volatility seems to be on continued decline since January 2015 despite some slight ups and downs since 2016 due to different events. For instance, one of major recent geopolitical development that coincided the Bitcoin's climb was the talks on "Brexit" that focus, nowadays, the attention of media and social networking[2].

[2] For details about how Bitcoin price reacts to the rise of doubts as to whether UK will vote to stay or to leave EU, you can refer to a recent analysis of Bouoiyour and Selmi (2016).

This article seeks to address whether there is a beginning of a mature crypto-market, or a calm period that precedes upheaval. To address this question, we compare how behaves Bitcoin price over two main periods: the first from December 01, 2010 to December 31, 2014, and the second from January 01, 2015 to July 20, 2016. To adequately measure the volatility of this complex phenomenon, we used an optimal GARCH model (a Component with multiple threshold-GARCH and Asymmetric-power GARCH, respectively, for the two periods under study) chosen via different information criteria with triggers to capture both the leverage and the regime switching features of the conditional variance process. By doing so, quite interesting results were drawn:

(i) For the period from December 01, 2010 to December 31, 2014, Bitcoin price appears too volatile. The conditional variance tends to follow an "explosive"process.

(ii) Since January 2015, the volatility of Bitcoin price becomes much less persistent (i.e., far from tending towards long-memory process).

(iii) For the two investigated periods, Bitcoin price dynamics seem more driven by negative (bad news) than positive shocks (good news).

Putting all these outcomes together, we support evidence that despite reaching a low volatility rate, Bitcoin market remains far from being mature. These results are not surprising. As a virtual currency in a nascent stage, Bitcoin may be linked to multiple risks of Bitcoin system. Precisely, Bitcoin is deeply sensitive to massive cyber-attacks that may play a destabilizing role in its system (Matonis 2012, Moore and Christin 2013). Bitcoin may also suffer from information asymmetry, as its system is relatively complex and thus may not be easily understood by all users (Ciaian et al. 2014). Being less volatile nowadays can be explained by the fact that proper security measures are becoming more practical for the public by ensuring that Bitcoin is as safe as possible.

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Appendices

Table A.1. GARCH extensions used in this study

Extensions	linear	nonlinear	symmetrical	Asymmetrical
GARCH-M (GARCH in mean, Bollerslev et al. 1993) $r_t = \mu_t + \varepsilon_t + \lambda\sigma_t^2$	x		x	
C-GARCH (Component GARCH Ding et al. 1993) $(\sigma_t^2 - \sigma^2) = \alpha(\varepsilon_{t-1}^2 - \sigma^2) + \beta(\sigma_{t-1}^2 - \sigma^2)$	x		x	
I-GARCH (Integrated GARCH, Bollerslev et al. 1993) $\sigma_t^2 = \omega + \varepsilon_{t-1}^2 + \sum_{i=1}^{q}\alpha_i(\varepsilon_{t-i}^2 - \varepsilon_{t-1}^2) + \sum_{i=1}^{p}\beta_j(\sigma_{t-j}^2 - \varepsilon_{t-1}^2)$	x		x	
T-GARCH (Threshold GARCH, Zakoian, 1994) $\sigma_t^2 = \omega + \sum_{i=1}^{q}(\alpha_i\lvert\varepsilon_{t-i}\rvert + \gamma_i\lvert\varepsilon_{t\_i}^+\rvert) + \sum_{i=1}^{p}\beta_j\sigma_{t-j}$		x		x
E-GARCH (Exponential GARCH, Nelson, 1991) $\log(\sigma_t^2) = \omega + \sum_{i=1}^{q}(\alpha_i z_{t-i} + \gamma_i(\lvert z_{t-i}\rvert - \sqrt{2/\pi})) + \sum_{i=1}^{p}\beta_j\log(\sigma_{t-j}^2)$				x
P-GARCH (Power GARCH, Higgins and Bera, 1992) $\sigma_t^\varphi = \omega + \sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^\varphi + \sum_{i=1}^{p}\beta_j\sigma_{t-j}^\varphi$	x		x	
A-PARCH (Asymmetric power ARCH, Ding et al., 1993) $\sigma_t^\varphi = \omega + \sum_{i=1}^{q}\alpha_i(\lvert\varepsilon_{t-i}\rvert + \gamma_i\varepsilon_{t-i})^\varphi + \sum_{i=1}^{p}\beta_j\sigma_{t-j}^\varphi$				x
CMT-GARCH (Component with Multiple Thresholds GARCH, Bouoiyour and Selmi, 2014) $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta(\omega + (\alpha + \gamma I_{(\varepsilon_{t-2}>0)})\varepsilon_{t-2}^2 + \beta\sigma_{t-2}^2)$		x		x

Notes: σ_t^2 : conditional variance, α_0 : reaction of shock, α_1 : ARCH term, β_1 : GARCH term, ε : error term; I_t: denotes the information set available at time t; z_t: the standardized value of error term where $z_t = \varepsilon_{t-1}/\sigma_{t-1}$; μ : innovation, γ : leverage effect; φ : power parameter.

Table A.2. Bitcoin price volatility: The optimal GARCH model chosen by information criteria

Period 1: from December 01, 2010 to December 31, 2014			
Models	Akaike criterion	Bayesian criterion	Hannan-Quinn criterion
GARCH	-5.4463	-5.1734	-5.3863
GARCH-M	-5.4374	-5.1761	-5.3719
I-GARCH	-5.4453	-5.1736	-5.4068
C-GARCH	-5.3076	-5.1733	-5.3869
CMT-GARCH	**-5.0731**	**-5.1493**	**-5.1071**
T-GARCH	-5.6021	-5.1612	-5.399
E-GARCH	-5.376	-5.1587	-5.3928
P-GARCH	-5.4639	-5.1715	-5.4059
AP-GARCH	-5.1067	-5.1622	-5.4219
Period 2: from January 01, 2015 to July 20, 2016			
GARCH	-5.3957	-5.0085	-4.9428
GARCH-M	-5.3682	-4.8774	-4.8212
I-GARCH	-5.5387	-4.9012	-4.8446
C-GARCH	-5.3512	-4.9447	-4.8661
CMT-GARCH	-5.3934	-5.1377	-4.8907
T-GARCH	-5.4131	-5.0849	-5.0097
E-GARCH	-5.6521	-5.0085	-4.9428
P-GARCH	-5.4017	-4.8774	-4.8215
AP-GARCH	**-5.2816**	**-4.8012**	**-4.7613**