Journal of Academic Research in Economics

Volume 11 Number 3 December 2019

ISSN 2066-0855

PROOFREADERS

CONTENTS

BUBBLES IN BITCOIN MARKET: AN EMPIRICAL INVESTIGATION

HAZGUI SAMAH
High Business School-Tunis, University of Manouba
E-mail: Hazguisamah066219@hotmail.fr

Abstract

The existence of bubbles has become a topical issue in finance and economics, particularly after the Subprimes crisis. In this study, we apply the test developed and presented by Phillips and al (2015, PSY) to investigate whether there exist multiple bubbles in the Bitcoin stock market, using monthly data. Our empirical results indicate that there did exist multiple bubbles in the bitcoin stock market. Further, the dates of the bubbles also corresponded to specific events in the stock market. Our results may have important implications for speculative investors, policymakers and law enforcement agencies alike.

Keywords: Bitcoin, Explosive bubbles, GSADF: Generalized Sup ADF.

JEL classification: F3, G1.

1. INTRODUCTION

The digital-currency bitcoin creation is attributed to Satoshi Nakamoto 2008. It is a new currency that overcomes the problems that beset traditional currencies. The use of crypto-currencies has gained traction in response to the perceived failures of government and central banks during the 2008 crash (Weber 2016). The Bitcoin is a transparent, free, fast, auto-regulated, anonymous, international network and secured by an “uncrackable” mathematical algorithms that control its supply which is set at a maximum of twenty one million units (Lo and Wang 2014). The market capitalization of bitcoin now stands at sixty billion dollar, the volume in circulation reaches at seventeen billion dollar and the circulating supply stands at seventeen million bitcoins in January 2019. In fact, bitcoin and other crypto-currencies may also offer cheaper alternatives to existing debit and credit card systems (Angel and McCabe 2015, Chaim and al 2019), in part reflecting recent technological innovations in regular monetary systems (Bohme and al 2015). From an economic perspective, its use may facilitate exchange and possibly save on transaction costs. Because of its exchangeability with fiat currencies such as the dollar, advantages could also come from speculative activity based on oscillations of the exchange rate. Amid huge public and media interest, individuals and organizations have increasingly begun to accept bitcoin and other digital currencies. Given all these qualities, it has been hailed as the future of money (Briere and al 2013).

2. RELEVANT LITERATURE

The financial and economic literature on crypto-currencies, such as bitcoin, has recently started to emerge (Cheah and Fry 2015, Vogiazas and Alexiou 2019) and is dwarfed by a multitude of popular articles and unpublished working papers. Forasmuch the strong fluctuations in bitcoin prices, several articles were interested in the detection and dating of bubbles on this market, like Cheah and Fry (2015) who find that the fundamental value of bitcoin is zero and the crypto-currencies are prone to substantial speculative bubbles from 17/07/2010 to 17/07/2014. Cheung and al (2015) show the existence of bubbles on this market and find a number of short-lived bubbles and three huge bubbles, the last of which led to the disappearance of the Mt Gox Stock Exchange in 2014. Fry and Cheah (2016) develop an econophysical model to reveal that bitcoin and Ripple (another crypto-currency) are characterized by negative bubbles in 2014. While recently, Corbet and al (2018) examine the fundamental drivers of the bitcoin price and show there are clear periods of bubble behaviour during the study period. Fry (2018) develops a rational bubble model for cryptocurrencies that combines heavy-tails with more realistic measures of risk and return from 01/01/2015 to 01/01/2018 and he find evidence of bubbles in bitcoin prices. From 01/01/2013 to 01/09/2018, Chaim and al (2019) conclude the existence of a bitcoin bubble from January 2013 to April 2014, but, the interesting thing, not at the end of 2017.

Since its first transaction in 2009, Bitcoin market has experienced a meteoric rise in its prices and has been accompanied by huge volatility swings, as can be seen in figure 2. Thus, the Bitcoin market could be characterized by bubbles which could burst anytime (Cheung and al 2015, Cheah and Fry 2015, Li and al 2019). In this paper, we provide empirical evidence to the existence of explosive bubbles in this market based on Phillips-Shi-Yu (2015) econometric technique. Our results confirm claims of the existence and burst of bubbles. Over the period 2010-2019, we detect two huge bubbles.

Our paper is organized as follow. This section introduces the relevant literature. Section 3 presents the data and describes the GSADF test methodology. Section 4 discusses empirical results. Section 5 concludes.

3. METHODOLOGY AND DATA

Most analysis of bubbles are using variance bounds test (Shiller 1981, Leroy and Porter 1981), west's two-step test (West 1987), cointegration test (Diba and Grossman 1988), intrinsic bubbles test (Froot and Obsterfeld 1991) and unit root tests which detect periodically collapsing bubbles. Phillips-Shi–Yu (2011) proposed an alternative approach named the Sup-Augmented- Dickey-Fuller

(SADF) test (figure 1). It is based on the idea of repeatedly implementing a right-tailed ADF test, but extends the sample sequence to a broader and more flexible range. The methodology consists to specify the following empirical *equation*:

$$y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{p} \varphi_i \, \Delta \, y_{t-1} + \varepsilon_t \qquad (1)$$

Where y_t is the variable in question, p is the maximum number of lags, μ is an intercept, φ_i for *i=1...p* are the differenced lags coefficients and ε_t is the error term.

Formally, $H_0: \delta = 1$

$H_1: \delta > 1$

For this, Philips-Shi-Yu (2011) use a sample interval of [0,1], the original sample is normalized by T, $ADF_{(r_1,r_2)}$ is the coefficient estimated by equation (1) and its corresponding ADF-statistic over the sample $[r_1, r_2]$, r_w is the fractional window size of the regression defined by $r_w = r_2 - r_1$ and r_0 is the fixed initial window.

The SADF test is based on recursive calculations of the ADF-statistics with a fixed starting point and an expanding window, where the r_0 set by the user. Next, the end point of the initial estimation window r_2 is set according the choice of minimal window size r_0 such that the initial window size is $r_w = r_2$, $r_2 \in [r_0, 1]$.

The SADF-statistic is defined as the supremum value of the ADF_{r_2} sequence for $r_2 \in [r_0, 1]$.

$$SADF_{(r_0)} = sup\{ADF_{r_2}\} \ , \ r_2 \in [r_0, 1] \qquad (2)$$

Then, Phillips and al 2015 suggested the Generalized SADF: GSADF (figure 1). This test generalizes the SADF test by allowing more exible estimation windows. Unlike the SADF procedure, the starting point, r_1, is also allowed to vary within the range $[0, \ r_2\text{-}r_0]$. Formally, the GSADF statistic is defined as :

$$GSADF_{(r_0)} = sup\{ADF_{r_1}^{r_2}\} \quad r_2 \in [r_0, 1], r_1 \in [0, \ r_2\text{-}r_0] \qquad (3)$$

When GSADF-statistic exceed the right tale critical value, the unit root null hypothesis is rejected in favor of explosive behavior. To identify, in graph, when a bubble occurs and collapses, we use the following strategy: the start date of a bubble is defined as the first observation on which the GSADF statistic is greater than the critical value of the GSADF statistic obtained from Monte Carlo or Bootstrap simulations, while, the end date of a bubble is defined as the first observation after that start date on which the GSADF statistic goes below the critical value. Similar definitions can be used for subsequent bubbles if there are more than one bubble in the data.

First of all, our GSADF critical value is obtained through Monte Carlo simulation. The above test assume Gaussian innovations with their unconditionnal variance being stationnary under both the null and alternative hypothesis. However, it is known that the series might be subject to permanent volatility shifts. In this case, the volatility break may have an impact on the size properties of the tests and results in a spurious rejection of the no bubble hypothesis. To conclude, the PSY procedure is a direct extension of the classical ADF unit root test with four distinguishing features. Firstly, the recursive estimate is known for its ability to use the data efficiently, which is why this procedure performs the ADF test repeatedly on subsamples of data recursively. Second, this test is used with adaptive (or rolling) sliding windows, since sliding windows are known for their ability to detect sudden or abrupt changes. Third, this procedure is estimated upstream (from T to 0) and not ahead (from 0 to T) to minimize the impact of the time periods that occurs and collapses. Fourthly, this test can be used as a warning system to indicate if there is an ex-ante bubble.

As regards, the Wild method or Harvey and al (2016) method introduced the non–stationnary volatility in the context of Phillips-Shi-Yu (2011) test and studied the impact of permanent volatility shifts on the preposed test. They find that the supremum bades test can be quite severely over sized and suggest a wild Bootstarp implementation. Briefly, we review the Bootstrap method in calculating the critical values. Under the null hypothesis, equation (1) can be written as :

$$\Delta y_t = \mu + \sum_{j=1}^{J} \varphi_j \; \Delta y_{t-1} + \varepsilon_t \tag{4}$$

Then the sample errors can be defined as ε_t=Δy_t if the coefficients for the autoregressive lags and deterministic components are constrained to zero and :

$$\varepsilon_t = \Delta y_t - \; \hat{\mu} - \sum_{j=1}^{p} \widehat{\varphi_J} \; \Delta y_{t-1} \tag{5}$$

Where μ and φ_j for *j=1, ..., p* are estimated by OLS. Then generate T observations of Bootstrap innovations. The innovations are defined as $\varepsilon_t^* = \omega \varepsilon_t$ where ω follows an i.i.d N (0, 1) independent of ε_t.

For the Sieve method or Gutierrez (2011) method, the innovations are resampled with replacements from the centered residuals $\varepsilon_t - \overline{\varepsilon_t}$ where

$$\varepsilon_t = (T - J - 1)^{-1} \sum_{t=2+J}^{T} \varepsilon_t \tag{6}$$

Then contruct the Bootstrap sample as

$$y_t^* = \sum_{j=1}^{T} \varepsilon_t^* \tag{7}$$

Where $y_1^* = 0$. Next, compute the test statistic for y_t^* and repeat the steps X times to drive the Bootstrap distribution of the test statistics. Finally, calculate the 90%, 95% and 99% quantities of the distribution of the different statistics.

Our data consists of monthly bitcoin closing prices collected from Bitcoin Coiundesk Index from 07/2010 to 01/2019 denominated in the US dollar. The choice of using the monthly data is justified by the fact that most of the previous studies were established in daily data. To avoid the problem of thin-trading in market, only the « log of » weighted prices are used.

4. EMPIRICAL RESULTS

Before following our tests, a graphical representation of our data is depicted in figure 2 and figure 3, which clarify the nature of the series. Figure 3 suggests that there is an upward trend with ups and downs with bitcoin prices in log scale. Table 1 reports the summary statistics of the variable. The mean (4.886187) and the standard deviation (3.125567) suggest that our variable is over-dispersed. However, no significant departure from normality is found as both kurtosis (2.789051) and skewness (-0.715852). Then, we use the Augmented Dickey Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin tests (KPSS). The results show that our variable is non-stationary in all cases (table 2). For example, if we allow for a trend in underlying data generating process, the ADF test clearly indicates that the variable is non stationary, so, it is the case where there is no drift term specified in the date generating process. In the case where a drift is allowed, the null hypothesis that there is a unit root cannot reject. That is why we need to run some tests like GSADF test that do not suffer from this limitation. As a first step in determining the existence of explosive periods and locating their exact origination and termination dates. The lag order in the estimation equation must be specified. Phillips-Shi–Yu (2011) argue that the asymptotic distribution of the test statistics remain the same when a low lag order is used, so they used a lag order of zero when conducting the forward recursive analysis with initialization of the first observation. Phillips and al 2015 demonstrate that adding lags order can potentially biases the estimation results and recommend obtaining the ADF test statistics with a lag of zero. Thus, we set the lag order to zero.

We run our test with a Monte Carlo simulation and the results are reported in table 3. This table shows that the GSADF statistic value, 3.155080, is greater than the critical values at the 90%, 95% and 99% confidence levels. This indicates that Bitcoin stock market is characterized by periodic bubbles or explosive sub-periods suggesting an explosive root and the existence of at least one bubble in every sub-sample. Figure 4 presents the GSADF test statistic together with its critical values at 95% critical values level over the sample period and confirms the evidence provided in table 3. The GSADF test statistic represented by the blue line shows that it exceeds its corresponding 95% critical values (denoted by the red line) two times over the sample period, suggesting that two episodes of bubbles are identified. The duration of bubbles ranges a few months. The first (occurred from December 2013 to April 2014) and the second one is long lived because it lasts more than a year (occurred from May 2017 to August 2018). It may be difficult to figure out how this bubbles started and busted but with the benefit of hindsight, it is possible to pin down incidents that may have led to these.

The rise of BTC since December 2013 is explained by the launch of the first bitcoin ATM machine in Vancouver (British Columbia), several states have started to give legal status to bitcoin like Germany and United Kingdom, many online and real merchants and services have started to accept it as a payment method such as Zynga, OkCupid, WorldPress, Reddit, TigerDirect, Foodler and Overstock.com...:

the price reaches its first historical value of 1216$. Which meant to the financial experts, a bubble and it was and dropped to 650$. The rise of bitcoin as of May 2017 was explained by the acceptance of bitcoin on Chinese platforms, the Managing Director of the FMI invited the Bank of England to take an interest in BTC, the French Ministry of Economy and Finance has listed bitcoin in its list of alternative payment methods, Japan recognizes the bitcoin as a legal means of payment, Russia announces that it will legalize its use, Norway's largest bank integrates accounts in bitcoin, CME announced plans to launch BTC futures, Wall Street Journal revealed that NASDAQ would consider launching BTC futures, Tokyo Financial Exchange has announced its intention to propose futures on the BTC, the National Council of the Principality of Monaco encouraged the experimentation of blockchains and cryptographic coins and BTC roses to more than 15 000$ in December 2017. While the incidents that caused the bursting of these bubbles are the following: the bankruptcy of MTGOX in 2014 (the first international trading platform of bitcoin) and the fierce debate in the United States in 2018 between the CFTC which is extremely favorable to this innovation and the SEC which is hostile.

To confirm our results, we run the test accounting for the sample size and changing volatility by considering the methods proposed by Harvey et al 2016 and Gutierrez 2011. The results are reported in table 4. There is an evidence of bubbles in the same periods as those obtained without considering the Bootstap methods. The GSADF statistic exceeds their critical values suggesting a bubble in Bitcoin stock market and these results are reconfirmed by their graphs (figure 5).

5. CONCLUSION

Amid growing levels of popularization (Fry 2018, Dimitri 2017, Chaim and Laurini 2019), policy makers and regulators are concentrated about the Bitcoin's disadvantages and its criminal possibilities. Some economists are concerned about the digital currency as a medium of exchange and some have argued that Bitcoin acts more like a speculative investment than a currency and some confirmed the role that speculation plays in the creation of asset bubbles and the destabilization of prices (Stein 1987, Shiller 1981). Our results show that crypto-currency market share a famous empirical facts with the other traditional markets-namely speculative bubble through an econometric investigation of the existence of bubbles in the Bitcoin market based on a recently developed technique of Phillips-Shi–Yu (2015) that has been shown to robustly detect bubbles. Their method detects stochastic explosive behavior of a given time series since such explosive feature is commonly shared by all bubbles. Despite its simplicity, this test provide, over the period 2010-2019, two huge bubbles in 2013 and 2017 lasting from 5 months to 15 months. Thus, our study confirms what investors, financial journalists and other participants in this crypto-market have been saying that Bitcoin has been in a bubble from 2017 (as a result of successive price ups and downs during 2017/2018). Bitcoin is difficult to value as its nature is not even clear: is it a commodity, currency or both? This is something that future researchers might want to take up**.**

REFERENCES

Abubakar, A., Kassim, S.H., & Yusoff, M.B. (2014). Financial development, human capital accumulation and economic growth: Empirical evidence from the Economic Community of West African States (ECOWAS). Global Conference on Business and Social Science, GCBSS.

Adamu, J.A., & Sanni, K. (2014). Stock market development and Nigerian economic growth. *Journal of Economic and Allied Fields, 2*(2) 116-132

Böhme, R., Christin, N., Edelman, B., Moore, M., (2015). Bitcoin: Economics, technology and governance. *Journal of Economic Perspectives*, *29*, 213-238.

Bouri, E., Molnár, P., Azzi, Q., Roubaud, D., & Hagfors, L.I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?. *Financing Researcher Letters, 20,* 192–198.

Chaim, P., & Laurini, M.P. (2019). Is Bitcoin a bubble?. *Physica A : Statistical mechanics and its applications*, *517* (1), 222-232.

Cheung, A., Roca, E., & Su, J.J. (2015). Crypto-currency bubbles: An application of the Phillips-Shi-Yu (2013) methodology on Mt. Gox butcoin prices. *Applied Economics*, *47*, 2348-2358.

Ciaian, P., Rajcaniova, M., & Kancs, D.A. (2016). The economics of Bitcoin price formation. *Applications Economics*, *48*, 1799–1815.

Corbet, S., *et. al.* (2018.a). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economic Letters*, *165*, 28-34.

Cheah, E.T., & Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economic Letters*, *130*, 32-36.

Fry, J., & Cheah, E.T. (2016). Negative bubbles and shocks in cryptocurrency markets. *International Review of Financial Analysis*, *47*, 343-352.

Fry, J. (2018). Booms, busts and heavy-tails: The story of Bitcoin and cryptocurrency markets?. *Economics Letters*, *171*, 225-229.

Harvey, D.I., Leybourne, S.J., Sollis, R., & Taylor A.R. (2016). Tests for explosive financial bubbles in the presence of non-stationary volatility, *Journal of Empirical Finance*, *38*, 548–574.

Li, Z.Z., Tao, R., Su, W.C., & Lobonţ, O.R. (2019). Does Bitcoin bubble burst?, *Quality and Quantity, Springer*, *53*(1), 91–105.

Phillips, P.C.B., Wu, Y., & Yu, J. (2011). Explosive behavior in the 1990s NASDAQ; when did exuberance escalate asset values*? International Economic Review*, *52*, 201–226.

Phillips, P.C.B., Shi, S., & Yu, J. (2015). Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P 500. *International Economic Review*, *56*(4), 1043-1078.

Phillips, P.C.B., Shi, S., & Yu, J. (2015). Testing for multiple bubbles: Limit theory of dating algorithms. *International economic review*, *56*(4), 1079-1134.

Tiwari, A.K., Jana, R.K., Das, D., & Roubaud, D. (2017). *Informational efficiency of Bitcoin – An extension*. *Economics Letters*, *163*, 106-109.

Yelowitz, A., & Wilson, M. (2015). Characteristics of Bitcoin users: An analysis of Google search data. *Applied Economics Letters, 22*, 1030-1036.

Economic notes : *Review of banking, finance and monetary economics*, vol. 48 (1).

Anex A

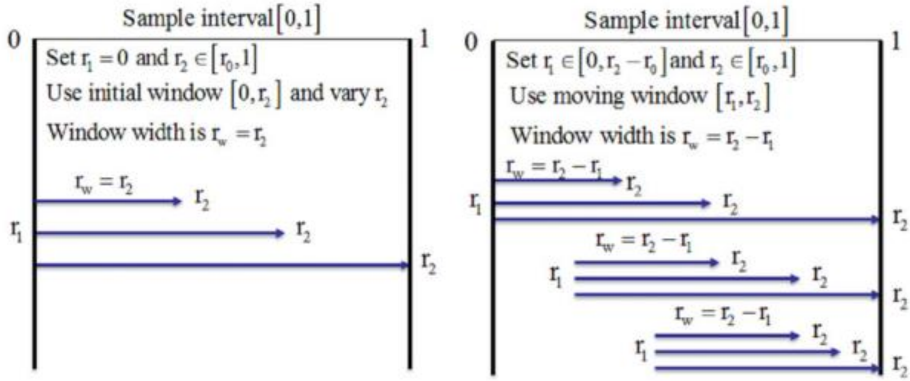


Figure 1. *Illustration of the SADF and GSADF procedures*

Source : Phillips and al, 2015, Testing for Multiple Bubbles: Historical Episodes of Exuberance and Collapse in the S&P 500, page 1049.

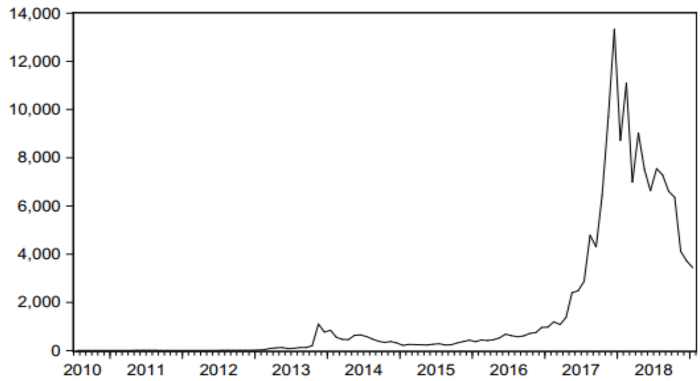


Figure 2. *Bitcoin prices over the sample period*

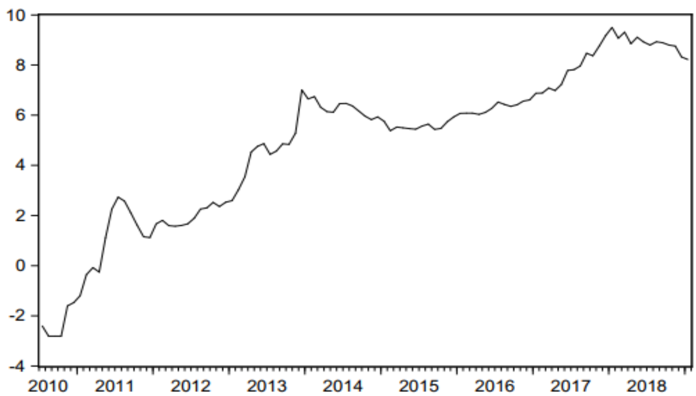


Figure 3. *Bitcoin prices in log scale over the sample period*

Table 1. *Summary Statistics*

VARIABLE	MEAN	ST.DEV	MIN	MAX	S.K	K.R	J.B
LNBTC	4.886187	3.125567	-2.813411	9.498344	-0.715852	2.789051	8.987923

Table 2. *Unit Root Tests*

Augmented Dickey Fuller test				
Test statistic	**1%critical value**	**5%critical value**	**10 %critical value**	**Underlying DPS**
-2.464781	-3.495677	-2.890037	-2.582041	CONSTANT
-2.000159	-4.050509	-3.454471	-3.152909	CONSTANT+TREND
1.025696	-2.587831	-1.944006	-1.614656	NONE
Phillips-Perron test				
Test statistic	**1%critical value**	**5%critical value**	**10%critical value**	**Underlying DPS**
-2.344759	-3.495677	-2.890037	-2.582041	CONSTANT
-2.178272	-4.050509	-3.454471	-3.152909	CONSTANT+TREND
0.680137	-2.587831	-1.944006	-1.614656	NONE
KPSS test				
Test statistic	**1%critical value**	**5%critical value**	**10%critical value**	**Underlying DPS**
1.127749	0.739000	0.463000	0.347000	CONSTANT
0.190153	0.216000	0.146000	0.119000	CONSTANT+TREND

Table 3. *Test for Explosive Behavior in the Bitcoin Market (Monte Carlo Simulation)*

Critical values	**Monte carlo simulation**
GSADF	3.155080***
99% level **95% level** **90% level**	2.313088 1.661485 1.414499

Notes: The table reports the GSADF test for the null hypothesis of a unit root against the alternative of an explosive root, with the initial window is set to 30 observations. The critical values for the test are obtained with 1000 replications.
*** indicates 1% significance.

Table 4. *Test for Explosive Behavior in the Bitcoin Market (Bootstrap Simulation)*

Critical values	**Bootstrap simulation**	
	Harvey et al 2016 method	**Gutierrez 2011 method**
GSADF	3.155080***	3.155080***
99% level **95% level** **90% level**	3.650945 2.600343 2.023162	2.612286 1.903561 1.531601

Notes: The initial window is set to 30 observations. The critical values for the test are obtained with 1000 replications.
*** indicates 1% significance.
** indicates 5% significance.

Figure 4. *Bubble detection and date-stamping using GSADF test (Monte Carlo simulation)*

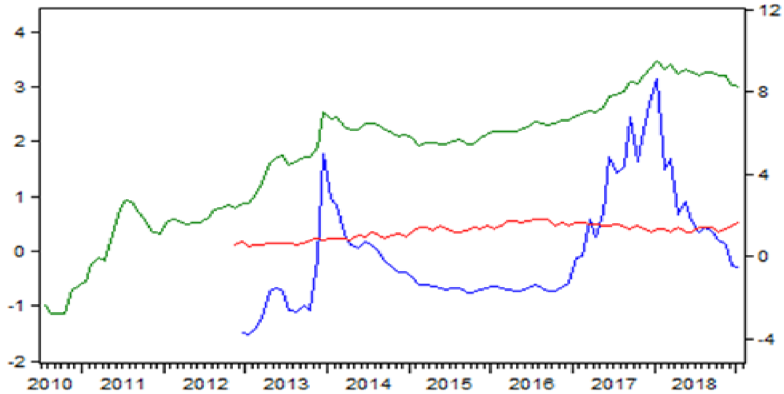
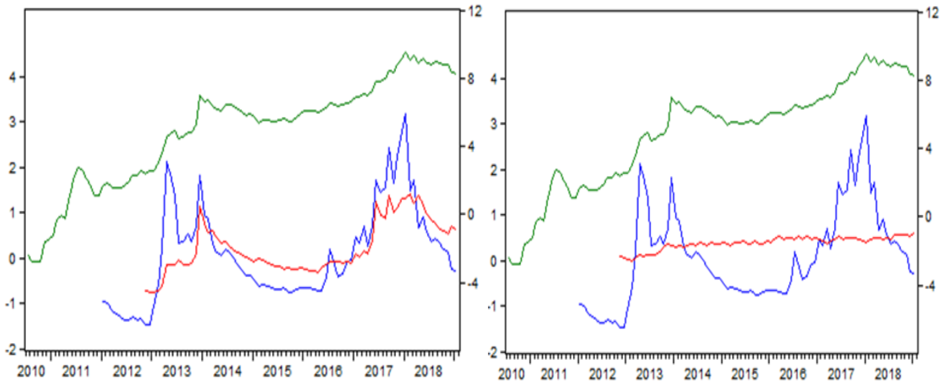


Figure 5. *Bubble detection and date-stamping using GSADF test (Bootstrap simulation)*



Harvey and al (2016) Method

Gutierrez (2011) Method