Bitcoin and gold prices: A fledging long-term relationship

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I. Introduction

Bitcoin has been the focus of many recent studies in the literature, mainly because of noticeable price development and market capitalization since 2016.Launched in November 2008 by Nakamoto (2008), this first open source digital currency in its most innovative form.

Its popularity has been keeping on growing particularly during the Great Recession in 2008-2010. Since then, several dimensions of Bitcoin have been widely investigated. There is especially a significant strand of the literature focusing on price formation (Ciaian *et al.*, 2016; Bouoiyour *et al.*, 2016;Bouri *et al.*, 2017b; Bouri *et al.*,2016; Kristoufek, 2013; van Wijk, 2014 among others) motivated by drastic price fluctuations. Bitcoin became also a prominent variable of interest in portfolio and investment management literature (Bouri et al., 2017a; Valstad and Vagstad, 2014; Eisl *et al.*, 2015), the digital currency considered as a speculative or investment vehicle (Baek and Elbeck, 2015), an alternative monetary system (Rogojanu and Badea, 2014), a diversifier to major stock indices (Bouri *et al.*, 2017a) or even a safe haven asset,in reference to any investment expected to retain or increase in value during market downturns (Bouri *et al.*, 2017b).

Such analyses about the abilities of Bitcoin led to a more recent strand in the literature that aims to compare Bitcoin with gold properties (Shen, 2018; Corbet *et al.*, 2018;Zhu, Dickinson and Li, 2017; Ciaian *et al.*, 2016; Dyhrberg, 2016; Glaser *et al.,* 2014; Greco, 2001). Scholars found commonalities and differencies between both. Dyhrberg (2016), for instance, foundthat both the commodities share commonalities which derive their value on account of their (i) scarcity, (ii) cost involvement in extraction, and (iii) no control of any specific government. These commonalities lead Popper (2015) to call the Bitcoin the digital gold. Besides, both commodities have a debatable intrinsic value (Katsiampa, 2017; Ciaian *et al.*, 2016; Glaser, 2014; Greco, 2001).While gold is primarily used for its store of value abilities, his safe haven abilities are often discussed in the literature. Bitcoinabilities remain even more uncertain.

Our paper aims to go a step further by assessing the role of gold in structurally predicting Bitcoin prices. A first study from Das and Kannadhasan (2018) investigated such relationship over the period July 2010 – March 2017 using a simple Ordinary Least Square (OLS) regression. They found a significant but weak negative causality that they explained by the fact that as a choice of an investment, risk-averse investors may prefer gold, while investors with speculative motive may prefer Bitcoin. The authors however omit the fact that Bitcoin prices are subject to high unconditional volatility, and that assuming linear relationship might be irrelevant. The authors might have had structural breaks over time leading then to spurious results.

Our paper brings two main contributions to the current literature. First, a methodological contribution since we use a threshold regressionto take into consideration potential structural breaks in our two series, after testing for the structural stability of the parameters based on recursive residuals and the cumulative sum of square (CUSUM) statistic.The paper appears therefore to complement the recent wave of studies using mainly generalized autoregressive conditional heteroscedasticity (GARCH) models (Katsiampa, 2017; Dyhrberg, 2016) or ordinary least square (OLS) approaches (Das and Kannadhasan, 2018).Second, we use the largest time span in the literature, from July 19. 2010 to December 31. 2018 which allows us take into account recent variations in the Bitcoin prices and reveal its structural relationship with gold prices.

The rest of the paper is organized as follows. Section II provides a data description. In section III, we present the methodology, while in section IV, we discuss empirical findings in light with the recent literature. Section V concludes.

II. Data description

We use daily data covering the period from the 19th of July 2010 to the 31st of December 2018 (3088 observations for each series). Bitcoin price data are collected from *Coindesk Price Index* while gold price data is sourced from *World Gold Council*. All data are labeled in U.S. dollars. Table 1 provides some summary statistics, and accordingly the average of Bitcoin over the period is 1525 dollars ranging from 0.05 in July 2010 to 18960.5 in December 2017, while it reaches 1354 dollars for gold ranging from 1049.4 in July 2015 to 1855 in August 2011. It may also be observed that mean returns are higher for Bitcoin than for gold. Standard deviation which stands for unconditional volatility shows that Bitcoin exhibits maximum volatility. Skewness coefficients for both Bitcoin and gold are positive higher for Bitcoin than gold, while the kurtosis coefficient of Bitcoin is positive suggesting the presence of a fat tail.

Table 1: Descriptive statistics

	Mean	St. Dev.	Skewness	Kurtosis	Min.	Max.	Obs.
Bit_pr	1525.1	2981	2.6	6.94	0.05	18960.5	3088
$Gold\_pr$	1354	185	0.9	-0.24	1049.4	1895	3088

Source: Authors' computation

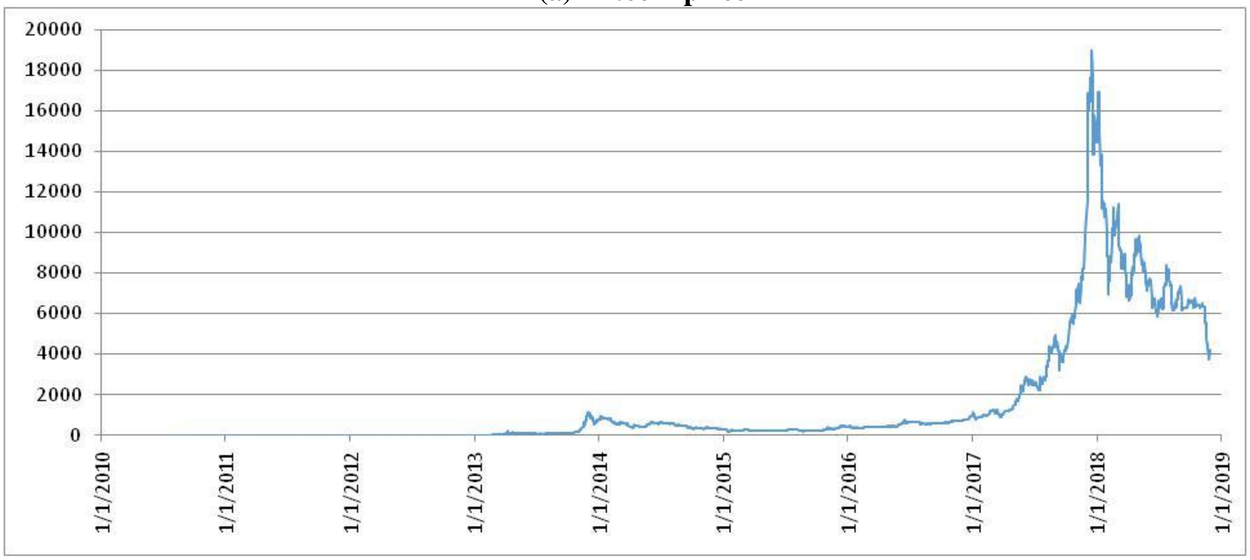
Notes: St.Dev. = Standard Deviation, Min. = Minimum, Max.=Maximum, Obs. = Number of observations.

Graphical representation of data is shown in Figure 1. It clearly shows an increase in the Bitcoin price, appearing as breaks in the data series trend in the beginning of 2017. 2017 appears a year of significant and rapid development of the Bitcoin. In August, the Bitcoin for the first time, traded above $4,000, gaining roughly 30% on that month. On the 18th of December, it reached $19,000, before starting to drop and to reach roughly an average of $8,000 during 2019. A series of concomitant announcements and decisions explain this erratic evolution. The main drivers of this rise are to find in the sudden rising Asian demand for the cryptocurrency, especially from China and Japan (Feng *et al.*, 2017). The Japanese government accepted in April 2011 Bitcoin as a legal payment method. Besides, Russian authorities announced their approval to legalize the use of cryptocurrencies such as Bitcoin and Norway's largest online bank *Skandiabanken* decided to integrate Bitcoin accounts. The drop in late December 2017 is mainly related to the lack of confidence of investors in the first upgrading phase of the blocksize.

The evolution in the gold price is volatile over the entire period but to a less extent. We distinguish a turning point in the beginning of 2013. Before this turning point –between April 2010 and February 2013, the regime is characterized by a high mean, while after that we note a downward slope associated with a low mean. The graphical relationship between our two series seems to evolve differently over the period. From pictorial analysis, it is reasonable to expect (i) the presence of a deterministic trendfor both series on one hand and (ii) one or more structural breaks on the other.

Figure 1: Graphical representation of data (July 19. 2010 – December 31. 2018)

(a) Bitcoin price



(b) Gold price

Source: Authors' computation

III. Methodology

This study uses the threshold regression model employed by Hansen (2000) and Chiu and Yeh (2017)to investigate the relation between Bitcoin and gold prices using time as the threshold variable.Such model is essentially concerned with modeling non-linearity, which is strongly suspected to characterize the relationship in our case. In other terms, it considers that time series data are divided into periods by turning points, meaning that the relationship between the dependent and independent variables is allowed to differ between periods. Besides, this model is robust to unknown forms of heteroscedasticity, something that cannot be said of the traditional Chow test (1960).

We conduct a two-step approach. As a first step, we estimate the linear relation between Bitcoin and gold prices, and continue by testing for its structural stability based on recursive residuals. Recursive residuals are defined as the difference between BIT and the first $t-1$ observations and can be used both to test for non-linearity and to test for structural breaks. The CUSUM (cumulative sum of squares) test (Brown *et al.*, 1975) is used in this study. Such new test for parameter stability in time series regressions helps indicate when and in what way breaks occur. It is expressed as follows:

$$W_t = \sum_{j=k+1}^{T} \frac{w_t}{\hat{\sigma}} \tag{1}$$

with

$$\hat{\sigma}^2 = \frac{\sum_{j=k+1}^{T}(w_t - \bar{w})^2}{T-k-1} \tag{2}$$

and

$$\bar{w} = \frac{\sum_{j=k+1}^{T} w_t}{T-k} \tag{3}$$

Where W_t is the cumulative sum of recursive residuals, T represents the number of observations, k represents the minimum sample size for which we can fit the model, w_t is the t^{th}standardized recursive residual.

The CUSUM statistic is calculated for each t and is plotted under the null hypothesis of model stability, given by the following form:

$$H_0: E(W_t) = 0 \tag{4}$$

If the sum goes outside a critical bound, it advocates that there is a structural break at the point at which the sum begins its movement toward the bound. Therefore the null hypothesis is rejected and the alternative one is accepted, suggesting that there are structural breaks in the series.

As a second step, once the presence of one or more structural break(s) is confirmed, we run the regression. We assume here that we identified one structural break –a two-regime regression-. The two-regime threshold regression equation is therefore expressed as follows:

$$BIT_t = (\alpha_1 gold_t) \times f(k_t \leq c_1^*) + (\alpha_2 gold_t) \times f(k_t > c_1^*) + \varepsilon_t \tag{5}$$

Where BIT_t is the Bitcoin price in time t, $gold_t$ is the gold price in time t, $f(.)$ is an indicator function, ε_t is an error term. We assume that if the relation (.) is true, then $f(.)$ equals 1, otherwise $f(.)$ equals 0. k_t and c_1^* represent the threshold variable and the optimal threshold value, respectively.

The optimal threshold valuec_1^* in the model can be determined by choosing the smallest residual variance ofequation (1):

$$c_1^* = \arg\min \hat{\sigma}^2 (c_t), t = 1, \dots, n \tag{6}$$

$$c_1^* \in [c, \bar{c}] \tag{7}$$

Where $\hat{\sigma}_t(c_t)$ is the residual variance from equation (1) with optimal threshold value c_1^*.

For robustness check, we run the Chow first test (1960) for parameter stability, commonly used in time series analysis despite its drawback in detecting unknown forms of heteroscedasticity. The test allows determining whether a single linear regression is more efficient than two separate regressions involving splitting the data into two sub-samples, from the break point. The test consists in estimating three different regressions, one over the whole period and then two for each sub-period. We obtain three sums of squared residuals that are used to run an F-test, with the parameter stability being null hypothesis.

IV. Results and Discussion

As explained in the methodology, we first start by using a basic linear model to examine the relation between Bitcoin and gold prices. Results displayed in table 2 indicate a significantly negative but weak ($\beta = -3.59$) relation between Bitcoin and gold prices, confirming that gold is a significant predictor of Bitcoin prices. The negative coefficient indicates that an increase in the price of gold lessens the price of Bitcoin. Such result is consistent with previous studies such as Das and Kannadhasan (2018).The underlying reason could be explained in two ways: first, investors prefer to invest in gold over Bitcoin, when gold prices show rising trends and second investors prefer to take lower risks with gold than with Bitcoin.

While the F-stat points out that all the variables are significant, the Ramsey RESET test shows that we can reject the null hypothesis and accept the alternative one suggesting that there are neglected nonlinearities in the model. It indicates a preliminary evidence of a nonlinear relation between Bitcoin and gold prices and on a bias in these linear results.

Table 2: Linear model's results

	Coefficient	**p-value**	**t-statistics**	**Standard errors**
Gold_pr	-3.59	0.00***	-12.67	0.28
Constant	6391.9	0.00***	16.49	387.6

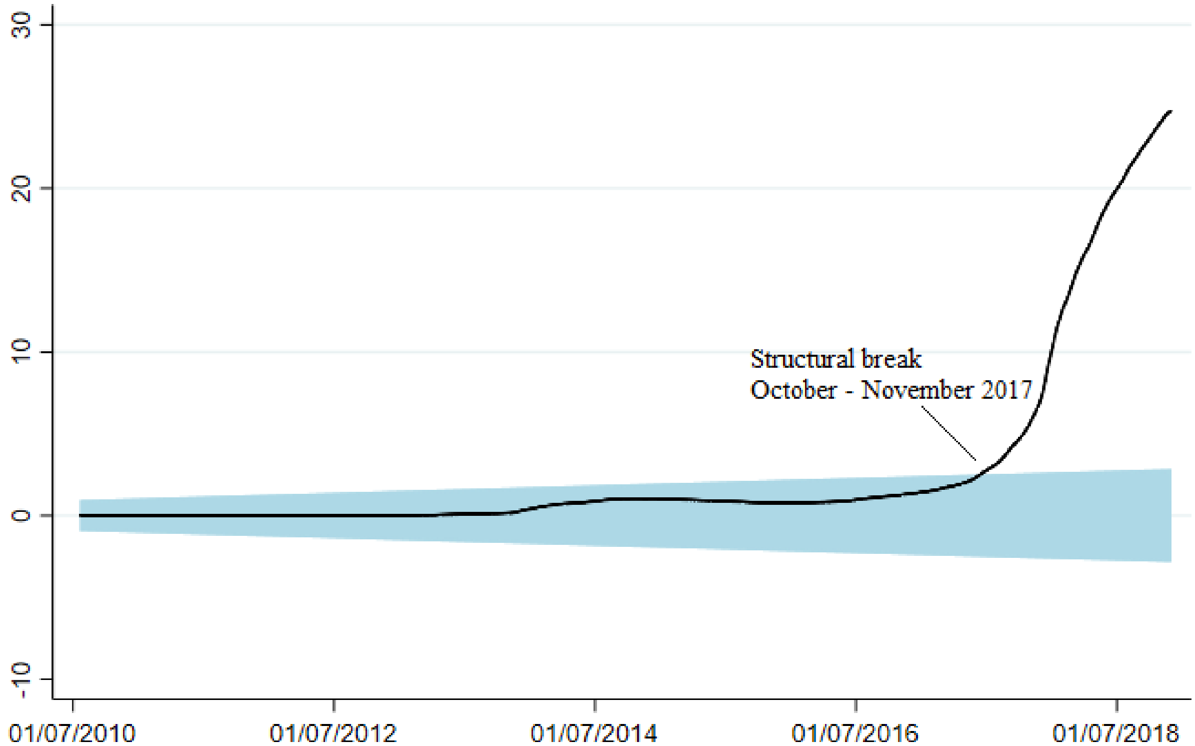
R-squared = 0.32
Adj. R-squared = 0.33
Number of observations : 3088
F test (H_0: The fit of the intercept-only model equals the model)
F(1, 3087) = 82.72
Prob> F = 0.000
Ramsey RESET test (H_0: There is no model misspecification)
F(3, 3095) = 60.31
Prob> F = 0.000

Source: Authors' computation

*Notes: *** denotes 1% level of significance.*

Going deeper into the analysis, we plot the recursive cumulative sum in Figure 2 and run a unit root test with structural break to statistically confirm the presence of one or more breaks in the relation, and to identify the period of this (these) potential break(s).

Figure 2: Recursive cumulative sum plot with 95% confidence bands around the null hypothesis (H_0: no structural break)



Source: Authors' computation

Figure 2 shows the results of the recursive cumulative sum test plot which includes a 95% confidence band around the null value. It indicates that the curvestructurally drifts outside the confidence band in the end of the plot, from the middle of 2017 to the end of our period (December 2018), which suggests that there are structural breaks in the relationship seemingly occurring around October – November 2017. The shape of the curve advocates for a hinge threshold, with a close-to-zero slope before the break.

Table 3 provides the output of the recursive cumulative sum test and reveals that the test statistic is larger than the 1% critical value so we would reject the null hypothesis that the mean is constant over time. Therefore, we accept the alternative hypothesis and confirm a nonlinear relation between Bitcoin and gold prices.

Table 3: Results of the cumulative sum test for parameter stability

	Test statistic	1% critical value	5% critical value	10% critical value
Recursive	8.23	1.1430	0.9479	0.850

Source: Authors' computation

Note: H_0: No structural break. Number of observations: 3088.
Sample: July 19. 2010 – December 31. 2018.

A unit root test with structural break is run to determine the date of the break. Results are displayed in table 4. The Wald statistics has a p-value lower than 1% indicating that we can reject the null hypothesis of no structural break and accept the alternative one. There is a structural break in the relationship between Bitcoin and gold prices which occurs on the 5th of October 2017. We saw from figure 1's description that such break is nourished on one side by an impressive growing trend in Bitcoin prices and a quite stable evolution in gold prices.Overall, the structural break can be interpreted as a market correction, a movement towards a different relationship between Bitcoin and gold prices which follows a temporary upswing in market prices.

Table 4: Unit root test with structural break

	Coefficient	p-value
Wald statistics	14002.9	0.00***
Estimated break date	05/10/2017	

Source: Authors' computation

Note: H_0: No structural break; *** denotes 1% significance level; 3088 observations.
Sample: July 19. 2010 – December 31. 2018.

As a second step of our methodology, we can now conduct the threshold regression with two distinct regimes (or one threshold) since we identified one optima structural break over the period.Table 5 displays the nonlinear results estimated using date as a threshold variable and the Akaike Information Criterion[1] (AIC, Akaike, 1975). The Chow test for parameter stability is also run as a robustness check.Results confirm gold as a significant predictor of Bitcoin prices for both regimes. In regime 1, it does have a negative relation with a low coefficient (-1.27 significant at 1% level) similarly to linear regression's results. In regime 2, however, the relation becomes positive associated with a high coefficient ($+22.09$ significant at 1% level). This means that an increase in demand for gold leads to an increase in demand for Bitcoin. The positive relationship of Bitcoin prices with gold prices could be explained as follows: first, it could indicate a concrete mutation of Bitcoin towards a safe haven. Traditionally, an increase in demand for gold is an indicator for an uncertain macroeconomic or financial environment in reference to the flight to safety phenomenon. Per analogy, Bitcoin might have become a hedge like gold despite its higher volatility. Identical features (Dyhrberg, 2016) seem to lead to identical properties. Second, it could confirm that Bitcoin became a concrete option for diversifying investors' portfolios. Investors do not secure their capital and preserve value through gold, but also through Bitcoin. After October 2017, one can reasonably assume that Bitcoin belong to the class of alternative investment options.

Table 5: Results of the threshold regression

		Coefficient	p-value	z-statistics	Standard errors
Threshold: 5/10/2017					
Regime 1					
	$gold\_pr$	-1.271	0.00***	-10.74	0.11
	constant	2192.12	0.00***	13.37	163.9
Regime 2					
	$gold\_pr$	$+22.09$	0.00***	18.86	1.17
	constant	-19830.0	0.00***	-13.30	1490.5
Chow test for parameter stability		F(3, 3081) = 5.05 with prob. > F = 0.0017			

Source: Authors' computation

Note: *** denotes 1% significance level. 3088 observations with 2595 observations under regime 1 and 494 observations under regime 2.

[1] Results using BIC and BQIC available upon request are similar to results using AIC.

Table 5 reports the result of the Chow test for parameter stability. We find evidence of a structural break on October 5. 2017 with a p-value equals to 0.0017. Therefore we confidently reject the null hypothesis that parameters are stable over time at the 1% significance level and validate our threshold regression.

V. Conclusion

This study uses cross-sectional data to investigate the Bitcoin-gold prices nexus over the daily period 2010 and 2018. This study contrastswith others in the previous literature, because it uses both linear and nonlinear threshold regression models and tests the structural stability of the parameters based on recursive residuals.

Empirical results indicate that gold is a significant predictor of Bitcoin prices. They indicate, however, that this impact is not linear over the period. A structural break occurring on the 5th of October 2017 implies in fact a two-regime relationship between Bitcoin and gold prices. Before the turning point, a significant negative and weak impact of gold on Bitcoin prices is found in line with previous literature (Das and Kannadhasan, 2018; Bouri *et al.*, 2017a). In that sense, Bitcoin was considered by investors more as a speculative asset than a hedge or safe haven one and was not challenging gold as a first-class safe haven asset. Nevertheless, after October 2017, an increase in gold prices predicts a significant, positive and strong impact on Bitcoin prices. A rise in the demand for gold, traditionally motivated by economic or financial uncertainty, increases the demand for Bitcoin. This indicates a radical change in the properties of the cryptocurrency which became a diversifier and a hedge.

Like many other studies, our research presents some room for further improvement. First, such results need be confirmed by investigating the Bitcoin – gold prices nexus in future, as at present the second period since October 2017 being six times shorter than the first one in our study. Second, global factors like oil prices or stocks indices which are barometers of macroeconomic and financial environment could also be included to design multivariate approaches and assess the property of safe haven of Bitcoin, beyond hedging.

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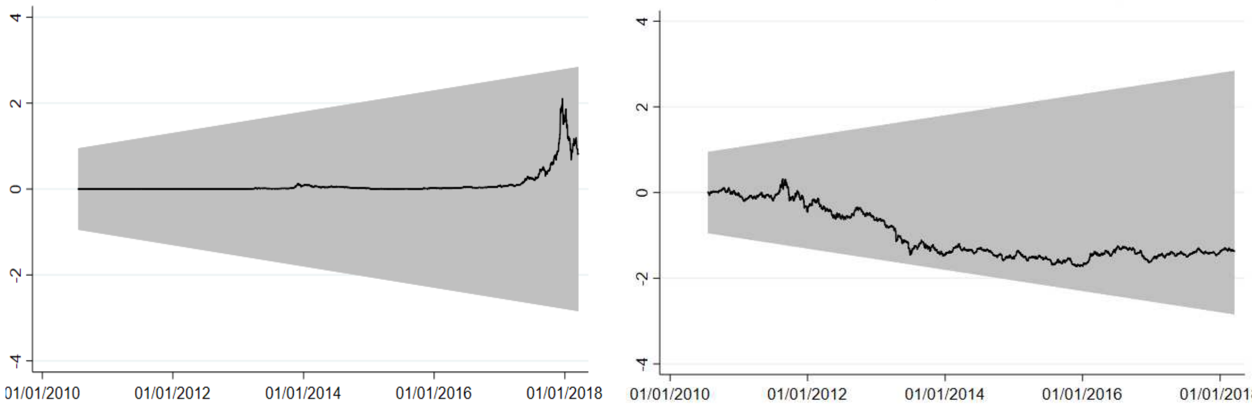
Appendix

Figure 1A: Recursive cumulative sum plot with 95% confidence bands around the null hypothesis (H_0: No structural break)

(a) D.bit_pr (b) D.gold_pr



Source: Authors' computation