DYNAMIC LINKAGES AMONG BITCOIN, GOLD PRICES AND EXCHANGE RATES OF US DOLLAR IN JPY, GBP AND CNY: DCC EGARCH APPROACH

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Abstract

The aim of this paper is to examine the relationship between bitcoin, exchange rates of US Dollar in JPY, GBP and CNY and gold prices. The daily data for the period of 19/07/2010 to 02/05/2018 are used to model volatilities between our variables with univariate and multivariate GARCH models (EGARCH, DCC-EGARCH). The results show that bitcoin has the benefits of both commodities and currencies in the financial markets and it is useful for portfolio and risk management.

Keywords: Bitcoin market, Gold price, Exchange rate EGARCH, DCC-EGARCH

JEL classification: D74, G14, G1, D24

1. INTRODUCTION

Since its creation in 2009, there is a huge interest in research addressing the economic-financial aspects of Bitcoin which evoked a debate on whether it is a currency or a commodity. As we know, Bitcoin is characterized by high levels of return and volatility which could affect other assets (European Central Bank,

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2012). Furthermore, a very little research has been written about Bitcoin and commodity, in general, and Bitcoin and gold, in particular. For example, Yermarck (2015) shows that Bitcoin is more like a speculative investment than a currency; whereas Polasik et al. (2015) show that Bitcoin is a medium of exchange. Monaghan (2018) consider Bitcoin as a bubble waiting to burst. Luther and Salter 2017 indicate that this cryptocurrency would be seen as an alternative to traditional stores of values, such as gold, and will be considered as a digital gold (Popper 2015). Baek and Elbeck (2015) found that Bitcoin returns are not influenced by fundamental economic factors, but by their investors. Brière et al. (2015) show the weak correlation of Bitcoin with alternative investments (commodities and hedge funds) and traditional assets (stocks, bonds, currencies) and show the diversification capabilities of Bitcoin despite its high volatility. Ji et al. (2017) show a low correlation between Bitcoin and gold market. Bouri et al. (2017) show that Bitcoin is a diversification for major world index, bonds, oil, gold and for American dollar. Li and Wang (2017) found a significant relationship in the short and long terms between the Bitcoin price and changes in economic fundamentals. Dyhrberg 2016 proves that Bitcoin has comparable hedging capabilities and safe havens like gold, and it would be categorized between gold and American dollar. Baur et al. (2018) criticize the paper of Dyhrberg (2016) and found that Bitcoin has different characteristics to gold and American dollars.

This review is structured as follows: Section 2 describes the data and the methodology and section 3 discusses the results of the estimated models which are followed by concluding remarks in section 4.

2. DATA AND METHODOLOGY FRAMEWORK

The daily data series used for this paper include 2844 observations from 19/7/2010 to 02/05/2018. The starting date is depicted by the accessibility of Bitcoin prices. The closing prices for the bitcoin index are sourced from coindesk.com. USD/JPY, USD/GBP and USD/CNY exchange rates are from Bloomberg data, gold prices are collected from the World Gold Council. For each data series, the daily returns are calculated as log (P_t)- log(P_{t-1}) where P_t is the daily closing price. Like Dyherberg (2016) study, we assume zero returns for Saturdays and Sundays to align all series with the Bitcoin data. In this paper, we use the EGARCH model of Nelson (1991) combined with DCC model to investigate the significance of asymmetry between the BTC, gold and American dollar. As known, one of the advantages of this model is that it allows engaging the dynamics of volatility, the volatility spill overs, the potential asymmetric effect of shock transmissions and the conditional correlations between series.

We apply in the first step the E-GARCH model to account for volatility feedback and leverage effects. According to Cappiello et al. (2006) the choice of univariate model will not affect the sign of the standardized residual and the correlations would be relatively insensitive to the GARCH model specification. The mean and variance equations take the following form:

$$Ret\text{-}BTCt = \beta_0+\beta_1 Ret\text{-}BTCt\text{-}1+\beta_2 GOLDt\text{-}1+\beta_3 USDEGBPt\text{-}1+\beta_4 USDJPYt\text{-}1+\beta_5 USDCNYt\text{-}1 +\varepsilon_t \qquad (1)$$

$$\ln(\sigma_t^2)=\lambda_0+ \lambda_1 GOLDt\text{-}1+\lambda_2 USDGBPt\text{-}1+\lambda_3 USDJPYt\text{-}1+\lambda_4\ USDCNYt\text{-}1+\alpha(\varepsilon_{t-1}/\sigma_{t-1})+ \gamma\ (|\varepsilon_{t-1}/\sigma_{t-1}| -\sqrt{2/\pi})+ \delta\ ln\sigma_{t-1}^2 \qquad (2)$$

Where ε_{t-1} denotes the previous period's squared residual series, α represents a magnitude effect or the symmetric effect of the model, δ measures the persistence in conditional volatility irrespective of anything happening in the market. The volatility takes a long time to die out following a crisis in the market when δ is large. The □ coefficient measures the leverage effect. If □<0 the good news generate less volatility than bad news and if □≠0, the impact is asymmetric.

Then, in a second step the standardized residuals are used to estimate the time varying correlations and the DCC model as formulated by Engle (2002) is estimated as :

$$H_t = D_t R_t D_t \qquad (3)$$

Where D_t =diag ($\square_{1.t}^{1\backslash 2}, \dots, \square_{n.t}^{1\backslash 2}$), R_t =diag($q_{1.t}^{1\backslash 2}, \dots, q_{n.t}^{1\backslash 2}$)$Q_t$($q_{1.t}^{-1\backslash 2}, \dots, q_{n.t}^{-1\backslash 2}$), H_t is an n×n conditional covariance matrix, R_t is the conditional correlation matrix and D_t is the diagonal matrix with time varying standard deviations on the diagonal.

The dynamic conditional correlation structure is modelled as follow:

$$Q_t = (1-\theta_1-\theta_2)\bar{Q} + \theta_1 Z_t Z_t' + \theta_2 Q_{t-1} \qquad (4)$$

Where, Q_t is the unconditional variance between series, $\bar{Q}$ is the unconditional covariance between the univariate series estimated in first step, θ_1, θ_2 are non-negative scalar parameters satisfying $\theta_1 + \theta_2 < 1$.

To determine the dynamic correlations between our variables, EGARCH and DCCEGARCH models are estimated with maximum likelihood estimation procedures. The likelihood function is maximized by Broyden, Fletcher, Goldfarb, Shanno (BFGS) numerical algorithms to estimate the parameters.

3. RESULTS AND DISCUSSION

This section presents all of the statistical procedures for the estimates of volatility measures according to the models presented in section 2. The results reported in Table 1 shows that both mean and volatility of the Bitcoin is greater than the other series suggesting that its return exhibit high volatility clustering with a standard deviation of 0.05867 following with gold by 0.008309, while CNY exhibit the very low volatility clustering. All return series are skewed negatively, except for the USD/GBP and USD/CNY. All series have kurtosis value in excess of that in a normal distribution. Table 1 also shows the results of unit root tests

over the return series. We perform the Augmented Dickey fuller (ADF) and Phillips Perron (PP) tests to check the property of the data series and in all cases we reject the null hypothesis of unit roots. Thus, all variables are stationary. This is also evident from the time series plot of return series which is presented in Fig 1. Table 2 reports the correlation coefficients of stock returns for period from July 19, 2010 to May 2, 2018. Across all of the asset returns, BTC correlates positively with other series except the gold. Note that the low or negative correlations between assets are desirable from a risk management perspective. The result from EGARCH model has reported in Table 3. From the mean equation it is confirmed that GOLD has positive impact on BTC at 1% level of significance suggesting that 10% increase in the GOLD leads to 21,49 % increase of BTC price. The coefficient on the exchange rates suggests that bitcoin returns are more sensitive to the value of the yen. Therefore, regional or country specific effects are presented. Moreover, this finding is similar to previous gold results (see Tully and Lucey 2007) and indicates that BTC may also be useful in hedging against the dollar like gold. Coming to the variance equations which indicate that positive volatility shock to the sterling and Yen exchange rates decreases the variance of the BTC returns which indicate that this cryptocurrency is a relatively safe asset in such situations. Thus, as already noted by Dyhrberg (2016), BTC may have some risk management capabilities like gold against the dollar (see Capie et al. 2005 results). Additionally, the estimated asymmetric term (γ) is positive and statistically significant confirming that good and bad news have not an asymmetric impact on the BTC volatility like gold (see Hammoudeh and Yuan 2008 results). Besides δ is positive and relatively large above 0.9, hence volatility takes a long time to die out. Added to this, table 3 displays weak levels of persistence ($\delta + \alpha < 1$) implying that the daily return series are stationary and absent of volatility clustering or market momentum. Lastly, the statistical significance of all the coefficients indicates the presence of conditional heteroskedasticity in the daily return series. As positive or negative shocks do not affect BTC and gold returns, it would be able to be used as a hedge market risks which affect other assets asymmetrically.

The second stage of the estimation uses the standardized residuals obtained from the E-GARCH univariate model to estimate the time-varying DCC correlations. Table 4 indicates that the time-varying correlations are mean reverting since $\theta_1+\theta_2<1$. The coefficient θ_1 measures the effect of past standardized innovations on dynamic conditional correlations, while θ_2 reports the impact of lagged dynamic conditional correlations on the current dynamic conditional correlations. In addition, these parameters are significant, indicating significant variation over the specified period. More specifically, the statistical significance of $\theta_1$and $\theta_2$indicates that a DCC model is suitable to be used. The estimated conditional correlations between variables shown in table 4 are very similar to the value recorded in table 3. The low values of θ_1 and the high values of θ_2 indicate that the correlation process is resistant to shocks and reverts to the mean quickly. This indicates that the correlations amongst the variables should be stable without many outliers.

4. CONCLUSION

The objective of this paper was to investigate the dynamic relationship between BTC, gold and American dollar from July 2010 to May 2018. The linear models fail to check the dynamics between such series due to serial correlation and non-normal distribution. Therefore, this paper investigates the time varying relationship between series using GARCH framework. The empirical results estimation reveals an interesting finding which has important implications for investors, portfolio managers and policymakers. Our finding contradicts with Kristoufek (2015) and Bouoiyour and Selmi (2015) who find insignificant relationship between Bitcoin and gold prices. However, they are in line with Li and Wang (2017) who show that Bitcoin is sensitive to macroeconomic indicators. This review shows that bitcoin is similar to gold and dollar and as bitcoin is decentralized it will never behave exactly like them on the market. Also, this cryptocurrency is similar to gold as it reacts to similar variables in the GARCH models, has similar hedging capabilities and similar react to news. However, the frequency is higher for bitcoin as its trading is faster and investors' reactions are quicker. To conclude, Bitcoin can combine some of the advantages of both in the financial market. Following Dyhrberg (2016) findings bitcoin would be between gold and American dollar. For future research we will be focus on the Bitcoin-stock nexus in China and Japan, which have a large part of Bitcoin trading activities and the inclusion of other cryptocurrencies will be an interesting addition to the current study.

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APPENDIX

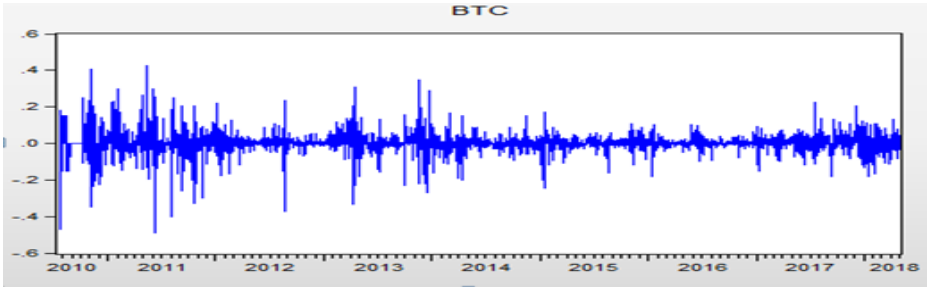
Table 1: *Summary Statistics and Stationarity Analysis*

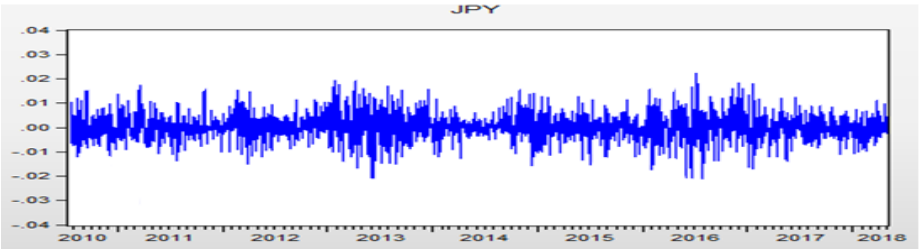
Statistics	**Ret-BTC**	**Ret-GOLD**	**Ret-JPY**	**Ret-GBP**	**Ret-CNY**
MEAN	0.004095	0.0000555	0.0000838	0.0000486	-0.0000239
S.D	0.05867	0.008309	0.005029	0.004656	0.001329
S.K	-0.352273	-0.782166	-0.068235	2.100088	0.569979
K.R	14.65598	14.93389	10.35179	42.83131	25.30690
MIN	-0.491528	-0.089128	-0.037722	-0.09962	-0.011890
MAX	0.424580	0.050705	0.034639	0.084006	0.018382
J.B	16158.47	17166.50	6406.990	190094.7	59119.31
Unit root tests					
ADF(none)	-8.141139***	-54.09615***	-53.23969***	-12.86731***	-53.20839***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
ADF(Constant)	-11.92291***	-54.09736***	-53.24888***	-12.88867***	-53.20427***
	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
ADF(Constant +Trend)	-11.99625***	-54.09615***	-53.23969	-12.91913***	-38.60425***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
PP(none)	-52.23889***	-54.10534***	-53.24347***	-53.21315	-49.45542***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PP(Constant)	-52.20812***	-54.09809***	-53.24982***	-53.20915***	-49.45471***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PP (Constant and Trend)	-52.22648***	-54.09716***	-53.24056***	-53.21169***	-49.45665***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

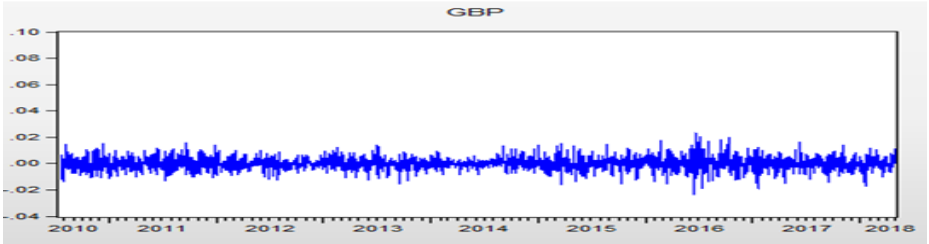
Note: S.D: Standard Deviation, S.K: Skewness, K.R: Kurtosis, J.B: Jarque- Berra, in the parenthesis we report p-values, *** denotes significance at 1% , 5% and 10% levels of significance.

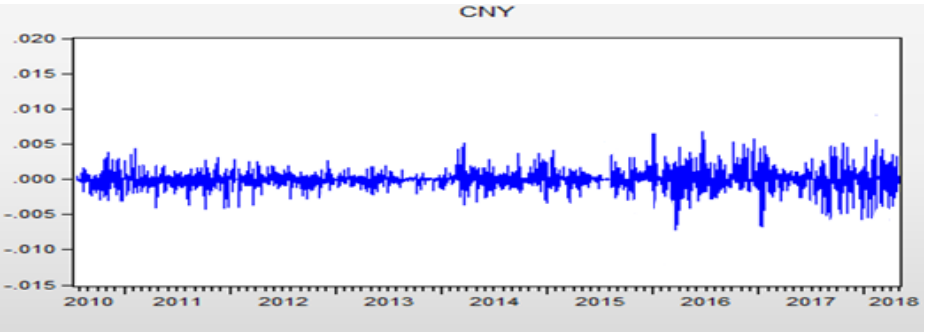
Table 2: *Correlation Matrix*

	Ret-BTC	Ret-GOLD	Ret-GBP	Ret-JPY	
Ret-CNY					
Ret-BTC	1				
Ret-GOLD	-0.001805	1			
Ret-GBP	0.012593	-0.005332	1		
Ret-JPY	0.018406	-0.037158	0.137312	1	
Ret-CNY	0.029419	-0.016980	0.174006	0.086009	1









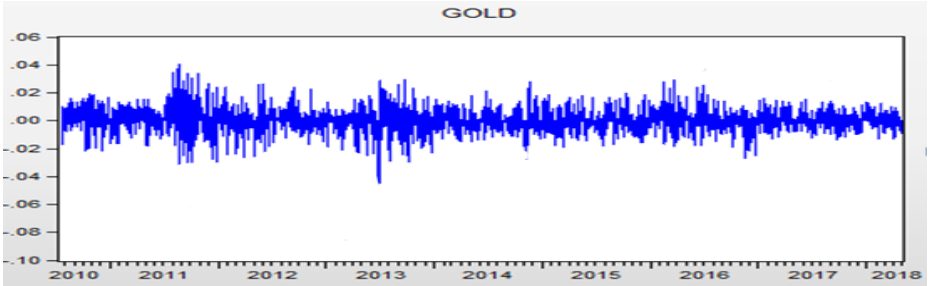


Figure 1. *BTC, gold and exchange rates returns*

Table 3: *Exponential Garch(1, 1) dependent variable return on bitcoin*

	Mean equation	**Variance equation**
GOLD*t*–1	0.214873***	2.035436**
	(0.046523)	(1.116042)
USD-GBP exchange rate*t*–1	0.159052	-15.02680***
	(0.119182)	(1.682186)
USD-JPY exchange rate*t*–1	-0.064496	-14.75246***
	(0.095588)	(1.885432)
USD-CNY exchange rate*t*–1	0.135846	29.09949***
	(0.432300)	(5.540160)
L.ar	0.043841***	
	(0.021307)	
L.earch α		*0.018349****
		(0.008186)
L.earch_a γ		*0.391582****
		(0.012524)
L.egarch		0.941722***
		(0.002930)
Constant	0.004323***	-0.620183***
	(0.000403)	(0.021203)

Note: *** indicates significance at 1% significance level , T-staistics in parentheses

Table 4: *Multivariate Garch Parameter Estimates*

Parameters	**DCC-EGARCH**
$\boldsymbol{\theta_1}$	**0.005732*** (0.001394)**
$\boldsymbol{\theta_2}$	**0.978194*** (0.008262)**
Loglikelihood	**52280.02**
Akaike info criterion	**-36.74263**
Hannan-Quinn	**-36.71847**

Note: *** indicates significance at 1% significance level , T-staistics in parentheses