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Bitcoin Hedging and Diversification Capabilities: An International Evidence

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Bitcoin Hedging and Diversification Capabilities: An International Evidence

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I. Introduction

Looking back in history from the internet and e-commerce to the virtual currencies we have enjoyed amazing advantages which changed our lives. Bitcoin, the famous crypto-currency since its launch after the financial crisis of 2008, has evolved the way we look at finance and our previous concepts to issue, store or transfer money. Despite the huge interest in Bitcoin as a digital asset, the current finance literature is still lacking empirical evidence on its hedging properties against other assets, in particular against major world equities. Indeed, this analysis will give detailed sight of the interaction of this new financial asset in the market and what place is has comparably to other assets. Bitcoin «*... is a peer-to-peer digital currency that trades on public exchanges and can be instantly transferred between any two people or more anywhere in the world with the speed of an email and at far lower cost than for transactions processed through the traditional financial system. The bitcoin launching was based on a nine-page "Bitcoin: A Peer-to-Peer Electronic Cash System" unleashing the bitcoin software, all of it public, in January 2009. The system allowed for the creation of 21 million bitcoins, total, with the last ones to be released in 2140*» (Debrova 2016). In this review, we will check Bitcoin from an economic view point. In this context, we note that this crypto-currency has compared to gold as they have many similarities: their primary values are given by their scarcity of supply, their supply is not controlled by any government, the both have high price volatility and their total supply is finite (Popper 2015, Dyhrberg 2016). Likewise, the gold has known by its hedging capabilities against stocks, bonds and American dollar, to this, Bitcoin might exhibit similar correlations. This paper addresses two questions: first, we examine whether Bitcoin acts as a hedge against the American dollar, to see how well Bitcoin protected against currency fluctuations and second, if Bitcoin can acts as a hedge for major world stock index. Consequently, this paper will thereby be modeled after previous researches of gold using the same methodology and our findings can be compared to get a sense of the comparable hedging capabilities of gold and «digital gold» (Dyhrberg 2016). The rest of the paper is organized as follow. Section 2 presents the relevant literature. Section 3 introduces the data and the methodology. Section 4 discusses the empirical results. Section 5 concludes.

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II. Relevant Literature

When we talk about the literature related to the hedging capabilities of a financial asset, we refer to the one linked to gold. Many studies have examined the dynamic relationship between gold, American dollar and stocks such as the first study which officially tests if gold is a hedge or safe heaven was done by Baur and Lucey 2010. They investigate that gold is a hedge against stocks from 1995 to 2005. Another study on this specific topic was done by Baur and McDermott 2010, who confirm that gold is a hedge for the American and major European stock markets but not for emerging stock markets from 3/2/1979 to 3/2/2009. Joy 2011 proves that the gold was a hedge against the American dollar during 23 years using 16 US dollar exchange rates from 01/10/1986 to 08/29/2008. Wang and al 2011 find the gold's ability to act like a hedge against yen/dollar exchange rate from April 1986 to March 2007 and investing in gold avert any possible loss. Ciner and al 2013, Arouri and al 2015, Choudhry and al 2015, Bredin and al 2015, Huang and al 2016 show that the gold can be regarded as an effectiveness hedge against the bond prices and equity index in China, German, UK and US markets changes. Mensi and al 2015, Ghazali and al 2015 show that the gold account in Malaysia and in the GCC (Gulf Cooperation Council: United Arab Emirates, Bahrain, Saudi Arabia, Qatar, Kuwait and Oman), provided a hedge competence to shariaa compliant markets. Jain and Biswal 2016 prove a strong relationship between gold and Indian stock, suggesting the importance of gold to limit stock market volatility confirmed by Bouri and al 2017 who show that there is a positive nonlinear relationship between gold and Indian stock market. Gürgün and Ünalmıs 2014, Nguyen and al 2016, Basher and Sadorsky 2016 and Iqbal 2017 prove the hedging ability of gold for many developing and emerging countries like Pakistan, Indian and European stock markets. Studies on the Bitcoin price formation became more relevant as well as their supply, demand and values increasing their impact on financial markets. Therefore there is an area of research which has received some attention in the literature is the relationship between Bitcoin and other financial assets, and determining whether Bitcoin can be classified as a diversifier or a hedge against other financial assets. Halaburda and Gandal 2014, Molnár and al 2015 and Eisl and al 2015 indicate the inclusion of highly volatile Bitcoin into a diversified portfolio is highly profitable and they predicate if some investors lose trust to the entire economy, they might resort to Bitcoin. This is one of the reasons why Bitcoin has sometimes been called digital gold (Popper 2015). Arguing 2015 show that Bitcoin is a hedge against UK equities and American dollar. Baur and al 2015 conclude that crypto-currencies and traditional asset classes are uncorrelated, making Bitcoin a useful diversification instrument in an investment portfolio. Brière and al 2015 found that the low correlation between Bitcoin and a diversified portfolio of assets can be useful as an investment strategy. Dyhrberg 2016a shows that Bitcoin can acts as a hedge, sharing similar hedging capabilities to gold, against the American dollar and the UK stock market. Dyhrberg 2016b compares asset capabilities and behavior of Bitcoin to those of gold and USD. She explains that Bitcoin is similar to gold in the way it reacts to news. Bouri and al 2017a prove that Bitcoin can be used as a hedge or a diversifier owing to the lowest connectedness between Bitcoin and other financial markets. Corbet and al 2017 find that Bitcoin, Ripple and Litecoin are not affected by external market shocks, thus, they are useful as a diversification and safe haven during the short run as they generate an increase in portfolio return. Added to this, there are a various ways used to discover the hedging capabilities of a financial asset against currency risk. To study the hedging capabilities of oil and gasoline spot prices against their futures prices, Chang and al 2010 use an OLS, a multivariate GARCH, an error correction and a state space models. Chang and al 2011 investigate the hedge ability of crude oil spot prices against their future prices by BEKK, CCC, DCC and VARMAGARCH models. Arouri and al 2011a, 2011b estimate a multivariate GARCH model to investigate first of all the volatility spillovers between oil, US and Europe stock markets over the period 1998 to 2009 and secondly between oil prices and stock markets in the Gulf Cooperation Council countries from 2005 to 2010. From January 1998 to December 2009, Arouri and al 2012 use a VAR-GARCH to model volatility dynamics between oil and European equity markets. Moreover, from January 2001 to December 2010, Sadorsky 2012 uses a multivariate GARCH model to investigate the volatility dynamics between the stock prices of technology companies, clean energy companies and oil prices. To study the hedging effectiveness between crude oil and related petroleum products, Pan and al 2014 estimate a regime switching asymmetric DCC (RS-ADCC) model. Lin and al 2014 model a VAR-GARCH and DCC-GARCH models to investigate the volatility dynamics between equity prices and oil prices in Ghana and Nigeria. To study the volatility transmission between emerging market stock, copper, oil and wheat prices over the period 2000 to 2012. Sadorsky 2014a estimates a multivariate GARCH models. Sadorsky 2014b estimates a DCC and CCC-GARCH models to model volatility and conditional correlations between the Dow Jones equity, gold and oil prices. Bredin and al 2015 employ a wavelet analysis and show that gold can be a hedge up to a year. Dyhrberg 2016a investigates the hedging properties of Bitcoin against stocks and American dollar by a GJR-GARCH and concludes that Bitcoin can reduce specific market risks and it is uncorrelated to stocks. To analyze the relationship between gold and global uncertainty Bouri and al 2017a apply a quantile regression approach and found that Bitcoin can hedge against global uncertainty at short investment horizons. Bouri and al 2017b employ a DCC-model and show the evidence of the limited hedging and safe properties of Bitcoin, although it can still be an effective diversifier.

III. Data and Econometric Modeling

We used for this study a daily data series from 19/07/2010 to 11/07/2018. The closing prices for the Bitcoin coindesk index are sourced from coindesk.com. USD/EUR, USD/GBP, USD/CNY and USD/JPY exchange rates are from Federal Reserve economic data, as well as the five most famous market indexes: FTSE100, SP500, DAX30, HSI and CAC40 are sourced from yahoo-finance. We filter out Bitcoin prices during periods when the currency markets are closed, since Bitcoin trades 24-hours a day, 7-days a week. We employ logarithmic returns for Bitcoin and other series such that: $r_t = \log P_t - \log P_{t-1}$ (1)

Where r_t are the returns, P_t is the price at time t and P_{t-1} is the price at time t-1.The descriptive statistics of the returns are reported in table 1. Where we can see the Bitcoin has the largest return and all the other series have a positive ones, except that of Chinese Yuan. In panel A, the variable with the smallest mean return is HSI while the SP500 has the highest mean return. In panel B, USD/EUR exchange rate has the smallest mean return while the USD/JPY exchange rate has the highest one. According to the standard deviation values, the Ret-BTC in panel A and in panel B is the most volatile series. In addition, we observe that RET-BTC and RET-CNY in panel A and B respectively has the highest level of kurtosis, indicating that extreme changes tend to occur more frequently for stock prices and the Jarque- Bera statistics reject normality for all our variables. Following Baur and McDermott 2010, Hood and Malik 2013, Ratner and Chiu 2013 we differentiate between a diversifier and a hedge as follow: « *a diversifier is an asset that has a weak positive correlation with another asset on average. A weak (strong) hedge is an asset that is uncorrelated (negatively correlated) with another asset on average*». Furthermore, our methodology is based to some extent on Dyhrberg 2016 who estimates a univariate GARCH model (T-GARCH) to investigate the hedging effectiveness of Bitcoin against the American dollar and FTSE index, on Chen and Wang 2017 paper which examines the dynamic relationship between gold and stock market in China using a multivariate model (DCC-GARCH) and on Bhatia and al 2018 who apply a DCC-GARCH and to check the robustness of the relationship, they estimate an ADCC-GARCH model between crude oil and precious metals.

Table 1: Summary statistics

Variables	Mean	S.D	Min	Max	Skewness	Kurtosis	J.B	Ob
Panel A								
Ret_ BTC	0.005475	0.070969	-0.619039	0.467597	-0.565764	17.29827	17563.42	2049
Ret_SP500	0.000462	0.008960	-0.068958	0.046317	-0.546761	8.231341	2438.542	2049
Ret_FTSE	0.000197	0.009310	-0.061994	0.039429	-0.314212	6.256756	939.2423	2049
Ret_DAX30	0.000365	0.012173	-0.070673	0.052104	-0.278632	5.783196	687.8427	2049
Ret_CAC40	0.000222	0.012289	-0.083844	0.068910	-0.263486	6.405952	1014.102	2049
Ret_HSI	0.000169	0.011149	-0.060183	0.055187	-0.357904	5.953191	788.3287	2049
Panel B								
Ret_ BTC	0.0059340	0.064762	-0.470040	0.499663	-0.029344	12.79516	8335.542	2085
Ret_EUR	0.0000073	0.005689	-0.029953	0.026398	0.018167	4.697595	250.4735	2085
Ret_GBP	0.0000252	0.005455	-0.029962	0.084006	1.782737	31.04006	69409.46	2085
Ret_JPY	0.0001170	0.005891	-0.037722	0.034639	-0.076096	7.505543	1765.568	2085
Ret_CNY	-0.0000096	0.001719	-0.010278	0.026954	1.841306	36.26811	97328.54	2085

Note: S.D: Standard Deviation, J.B: Jarque- Berra, OB: observations

This section describes the econometric modeling procedure we use to assess the hedge properties of Bitcoin. First, we apply the threshold Garch (T-GARCH) or named also the Glosten-Jagannathan-Runkle (GJR-GARCH) introduced by Glotsen and al 1993, and as suggested by Engle and Ndong 1993, this model is the best ARCH model which check the asymmetric impact of new information on two return volatility. Then, to estimate the volatility dynamics and conditional correlations between the return series, we use the DCC model of Engle 2002 and the ADCC-GARCH model of Cappiello and al 2006. Firstly, all variables have been including in a cross-correlogram to investigate the Bitcoin hedging capabilities then we will confirm the dynamic relationship with a T-GARCH model. The mean equation (2) and the variance equation (3) are shown below as:

$$\Delta lnBTC_t = \beta_0 + \beta_1 \Delta ln\mathrm{BTC}_{t-1} + \beta_2 \Delta \ln exchange\ rate_t + \beta_3 \Delta lnexchange\ rate_{t-1} + \varepsilon_t \quad (2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \lambda\, d_{t-1} \varepsilon_{t-1}^2 + \beta_0 \sigma_{t-1}^2 \quad (3)$$

Secondly, we will analyze the relationship between the return on Bitcoin and each index and identify if this crypto-currency can be used as a hedge. The mean equation (4) and the variance equation (5) are shown below as:

$$\Delta lnBTC_t = \beta_0 + \beta_1 \Delta lnBTC_{t-1} + \beta_2\, \Delta ln\ index_t + \beta_3 \Delta ln\ index_{t-1} + \varepsilon_t \quad (4)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \lambda\, d_{t-1} \varepsilon_{t-1}^2 + \beta_0 \sigma_{t-1}^2 \quad (5)$$

Unlike Baba-Engle-Kraft-Kroner (BEKK) and constant conditional correlation (CCC) models, which may have unreasonable parameter estimates and convergence problems, the model of Engle 2002 has the ability to check the dynamic relationship across return series vwith fewer computational complications (Parhizgari and Cho 2008). A DCC model is estimated in two steps: in the first step, a univariate GARCH (1, 1) model is estimated. In the second step, a time-varying correlation matrix is computed using the standardized residuals from the first-step estimation. However, for the purpose of this study the model is estimated separately for pairs of return series. In doing so, the minor possibility of getting biased estimates of parameters in higher dimensions is prevented (Hafner and Reznikova 2012). The mean equation of the DCC model is specified as:

$$r_t = \mu + a r_{t-1} + \varepsilon_t \qquad (6)$$

The residuals are modeled as:

$$\varepsilon_t = H_t^{1\backslash 2} Z_t \qquad (7)$$

Where H_t is the conditional covariance matrix of r_t , Z_t is a n×1 i.i.d random vector of errors. All DCC class models (including the conditional correlation GARCH (CCC)) use the fact that H_t can be decomposed as follow: $H_t = D_t R_t D_t$ (8)

Where; H_t is an n×n conditional covariance matrix, R_t is the conditional correlation matrix, D_t is the diagonal matrix with time varying standard deviations on the diagonal.

$$D_t = \mathrm{diag}(\, h_{1.t}^{1\backslash 2}, \dots, h_{n.t}^{1\backslash 2}) \quad R \qquad (9)$$

$$R_t = \mathrm{diag}(\, q_{1.t}^{1\backslash 2}, \dots, q_{n.t}^{1\backslash 2}) Q_t (\, q_{1.t}^{-1\backslash 2}, \dots, q_{n.t}^{-1\backslash 2}) \qquad (10)$$

Where the expressions of h are the GARCH (1,1). For the univariate GARCH model the elements of H_t are written as:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1} + \beta_i h_{i,t-1} \qquad (11)$$

The symmetric positive definite matrix is modeled as:

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 Z_t Z_t' + \theta_2 Q_{t-1}) \qquad (12)$$

Where $\bar{Q}$ is the n×n unconditional correlation matrix of the standardized residuals $Z_{i,t} = \varepsilon_{i,t} / \sqrt{h_{i,t}}$ The DCC model is mean reverting as long as $\theta_1 + \theta_2 <$ 1. For the purposes of this paper, the focus of interest is the conditional correlations between the return of Bitcoin and return of each other series pair are calculated by:

$$\rho_{i,j,t} = q_{i,j,t} / \sqrt{q_{i,i,t+q_{j,j,t}}} \qquad (13)$$

Capiello and al 2006 estimate the asymmetric DCC (ADCC) - GARCH model and the dynamic regression is given by:

$$h_{i,t} = \omega_i + \alpha_i h_{i,t-1} + d_i \varepsilon_{t-1}^2 \, I(\varepsilon_{i,t-1}) \qquad (14)$$

Where $I(\varepsilon_{i,t-1})$ equal to 1 if $\varepsilon_{i,t}$ <0 and equal to 0 otherwise. The asymmetric effect is designed to capture an often observed characteristics of financial assets that an expected fall in prices tend to increase volatility more than an expected increase in asset prices of the same magnitude meaning that bad news increases volatility more than good news and the dynamic of Q in this case are given by:

$$Q_t = (\bar{Q} - A'\bar{Q}A - B'\bar{Q}\,B - G'\overline{Q^-}G) + A' Z_{t-1} Z_{t-1}' A + B' Q_{t-1} B + G' Z_t^- Z_t'^- G \qquad (15)$$

Where A, B, G are n×n parameters matrix. Z_t^-, $Z_t'^-$ are zero threshold standardized errors which are Z_t equal to when less than 1 and 0 otherwise. $\bar{Q}$, $\overline{Q^-}$ are the unconditional matrix of Z_t, Z_t^-.

IV. Empirical Results

Table 2 reports the cross-correlations between Ret-BTC/Ret-variables for up to four lags. The most of coefficients are negative suggesting that Bitcoin can be used as a hedge against these assets. However, these correlations are very smalls, thus suggesting, that any dynamic relationship, if it exists, will be short lived. Capie and al 2005 found similar small negative values of correlations between the return on the yen dollar and sterling dollar exchange rates and the return on gold, proving the gold as the «anti-dollar». Next, by estimating the TGARCH we can verify in more details this relationship.

Table 2: Cross-correlogram between Ret_Bitcoin and Ret_variables

	BTC/SP500	BTC/DAX	BTC/FTSE	BTC/HSI	BTC/CAC	BTC/EUR	BTC/GBP	BTC/JPY	BTC/CNY
k=-4	-0.0104	0.0034	0.0092	0.0200	-0.0023	0.0028	-0.0010	-0.0224	-0.0186
k=-3	0.0488	0.0226	0.0105	-0.0154	0.0060	0.0013	-0.0055	-0.0042	-0.0393

k=-2	-0.0136	0.0271	0.0305	0.0121	0.0348	-0.0287	-0.0298	0.0136	-0.0231
k=-1	-0.0138	0.0006	-0.0370	0.0010	-0.0091	-0.0083	-0.0020	0.0132	0.0003
k=0	0.0382	0.0110	0.0157	-0.0197	-0.0061	-0.0012	0.0182	0.0130	-0.0080
k=1	0.0519	0.0462	0.0406	0.0117	0.0583	0.0083	-0.0110	-0.0012	0.0255
k=2	-0.0260	-0.0013	0.0051	0.0418	-0.0021	0.0297	-0.0113	0.0296	-0.0292
k=3	0.0356	0.0145	0.0004	-0.0287	-0.0035	-0.0134	-0.0045	0.0005	-0.0215
k=4	0.0243	0.0462	0.0384	0.0343	0.0518	0.0021	-0.0086	0.0037	0.0248

Table 3 suggests that Bitcoin has hedge ability against US dollar fluctuations as the contemporaneous effects and their lagged coefficients are insignificant, implying that these variables are uncorrelated on average, thus, the BTC is a weak hedge and has long-term hedge capabilities. The return on BTC is not affected by changes in the exchange rates which creates a possibility for investors to hedge some of the market risks. These results are similar to those of Capie and al 2005 though they get insignificant contemporaneous and lagged values, indicating that Bitcoin and gold have similar hedging capabilities against the American dollar.

Table 3: T-GARCH (1,1) with exchange rates and dependent variable return on BTC

Variables	**Mean equation**	**Variance equation**
Ln$(USD/EUR)_t$	0.038549 (0.100448)	
Ln$(USD/EUR)_{t-1}$	-0.032254 (0.094166)	
L.ar	0.032183** (0.012898)	
L.arch α		2.756021 (4.761759)
L.tarch λ		-1.082271 (1.911593)
L.garch β		0.771238*** (0.018386)
constant	0.002164*** (0.000518)	0.000204 (0.000346)
Ln$(USD/GBP)_t$	0.061959 (0..099371)	
Ln$(USD/GBP)_{t-1}$	0.017411 (0.094132)	
L.ar	0.031805** (0.01287)	
L.arch α		2.875871 (5.194654)
L.tarch λ		-1.134033 (2.090081)
L.garch β		0.771414*** (0.018336)
Constant	0.002136*** (0.000518)	0.000210 (0.000373)
Ln$(USD/Yen)_t$	-0.001978 (0.086476)	
Ln$(USD/Yen)_{t-1}$	-0.005824 (0.084318)	
L.ar	0.031913** (0.012896)	
L.arch α		2.718128 (4.638141)
L.tarch λ		-1.063486 (1.856400)
L.garch β		0.771309*** (0.018390)
constant	0.002161*** (0.000519)	0.000202 (0.000339)
Ln$(USD/Yuan)_t$	-0.165045 (0.290384)	
Ln$(USD/Yuan)_{t-1}$	0.168793 (0.294288)	
L.ar	0.032138** (0.012886)	
L.arch α		2.770164 (4.794982)
L.tarch λ		-1.087227 (1.923993)
L.garch β		0.770648*** (0.018416)
constant	0.002159*** (0.000518)	0.000203 (0.000346)

*Note: * p<0.1, ** p<0.05, ***p< 0, standard errors in parentheses*

Table 4 summarizes the results of the estimated models 4 and 5. In the mean equations, the contemporaneous effects of SP500, FTSE100, CAC40 and HSI and their lagged coefficients are insignificant; thus, these variables are uncorrelated on average implying that the BTC is a weak hedge against their fluctuations in long term. In addition, the contemporaneous effect is significant and positive between BTC/DAX30 which means that they are correlated on average and the BTC is not a means of hedging against its fluctuations.

Table 4: T-GARCH (1, 1) with index and dependent variable return on BTC

Variables	Mean equation	Variance equation
$\text{Ln}(USD/SP500)_t$	0.039024 (0.061333)	
$\text{Ln}(USD/SP500)_{t-1}$	0.077658 (0.061824)	
L.ar	-0.032209 (0.020087)	
L.arch α		109.3581 (7843.090)
L.tarch λ		-22.95347 (1646.668)
L.garch β		0.758723*** (0.017959)
Constant	0.001749*** (0.000504)	0.007576 (0.542918)
$\text{Ln}(USD/FTSE)_t$	0.062362 (0.054574)	
$\text{Ln}(USD/FTSE)_{t-1}$	0.037520 (0.054633)	
L.ar	-0.031468 (0.020118)	
L.arch α		105.1226 (7587.824)
L.tarch λ		-21.96385 (1570.824)
L.garch β		0.757413*** (0.018077)
Constant	0.001765*** (0.000505)	0.007702 (0.550265)
$\text{Ln}(USD/DAX30)_t$	0.088492** (0.042350)	
$\text{Ln}(USD/DAX30)_{t-1}$	0.047706 (0.042035)	
L.ar	-0.032028 (0.020062)	
L.arch α		110.6413 (7930.781)
L.tarch λ		-23.62137 (1693.653)
L.garch β		0.758519*** (0.017926)
Constant	0.001781*** (0.000502)	0.007556 (0.541204)
$\text{Ln}(USD/CAC40)_t$	0.036586 (0.041018)	
$\text{Ln}(USD/CAC40)_{t-1}$	0.044229 (0.040756)	
L.ar	-0.032029 (0.020112)	
L.arch α		108.4442 (7778.453)
L.tarch λ		-22.64406 (1624.669)
L.garch β		0.758416*** (0.017934)
Constant	0.001774*** (0.000502)	0.007393 (0.529896)
$\text{Ln}(USD/HSI)_t$	-0.015261 (0.044896)	
$\text{Ln}(USD/HSI)_{t-1}$	0.072571 (0.045860)	
L.ar	-0.031630 (0.020084)	
L.arch α		107.4556 (7709.482)
L.tarch λ		-21.90181 (1571.842)
L.garch β		0.758041*** (0.018007)
Constant	0.001776*** (0.000503)	0.007775 (0.557419)

*Note: * p<0.1, ** p<0.05, ***p< 0, standard errors in parentheses*

Next, we estimate the multivariate GARCH model of dynamic conditional correlations using maximum likelihood. Since the series in our dataset show some evidence of non-normality, the remedy here is to use the quasi maximum likelihood method (Bollerslev and al 1988) in order to generate consistent standard errors that are robust to non-normality. However, to account for non-normality in the distribution of returns the DCC-GARCH and ADCCGARCH was estimated with a multivariate t-student distribution. Table

5 reports DCC and ADCC-GARCH parameter estimates. For the DCC model the estimated coefficients θ_1 and θ_2 sum is less than one, indicating that the dynamic conditional correlations are mean reverting. Thus, in panel A, the dynamic correlation between BTC and USD/GBP (0,977) was the strongest, while the dynamic correlation between BTC and USD/CNY (0.883) was the weakest. In panel B, the dynamic correlation between BTC and FTSE100 (0,326) was the weakest, while dynamic correlation between BTC and HSI (0,985) was the strongest. In the case of the ADCC model, the dynamic conditional correlations are also mean reverting. ADCC parameter estimate (θ_3) for asymmetric relationship is not statistically significant and suggests that volatility estimates between Bitcoin and the other financial assets are not influenced by negative shocks or sharp increase in returns. To provide more information about the correlation dynamics, the summary statistics for the derived correlations are presented in Table 7.

Table 5: DCC-GARCH/ADCC-GARCH models of each crypto-currency Bitcoin/Asset pair

Variables	Symmetric DCC-GARCH		Asymmetric DCC-GARCH		
	θ_1	θ_2	θ_1	θ_2	θ_3
PANEL A					
BTC/JPY	-0.014096	0.954584	-0.015519	0.833332	0.007817
	(0.023423)	(0.093241)	(0.009104)	(2.528956)	(0.054071)
BTC/GBP	-0.005187	0.982619	-0.007451	0.793580	0.032418
	(0.004492)	(0.041953)	(/)	(/)	(/)
BTC/EUR	-0.022613	0.913685	-0.019531	0.948916	0.015861
	(0.030966)	(0.140065)	(0.037174)	(0.102658)	(0.030263)
BTC/CNY	0.022927	0.860495	-0.002572	0.758424	0.075901
PANEL B	(0.040692)	(0.184504)	(0.005166)	(0.270693)	(0.102756)
BTC/SP500			0.076272	0.709112	-0.056543
	0.039013	0.749828	(0.236363)	(0.876427)	(0.284955)
BTC/DAX30	(0.150259)	(1.009953)	0.001298	0.813735	0.013693
	0.009321	0.822222	(0.295177)	(2.730911)	(0.405286)
BTC/FTSE	(/)	(/)	-0.042036	0.783839	0.060379
	-0.038767	0.365096	(0.016214)	(0.528017)	(0.178285)
	(0.149989)	(2.853451)			
BTC/CAC40	0,034543	0,790155	-0.004175	0.891528	-0.002758
	(0,286954)	(59,56839)	(0.114745)	(1.369894)	(0.030671)
BTC/HSI	-0.01606	1.001130	-0.025027	0.993308	-0.014010
	(0.292666)	(0.007693)	(/)	(/)	(/)

Note: Standard errors in parentheses, (/) indicates it could not be estimated

The magnitude of mean dynamic conditional correlation coefficients varied between -1 and 1. If the coefficient was closer to -1, the negative correlation between Bitcoin and financial assets was stronger. In contrast, when the coefficient was closer to 1, the positive correlation between Bitcoin and other series was stronger. If the coefficient was equal to 0, Bitcoin had no relationship with them. The mean dynamic conditional correlations between stock index, American dollar and Bitcoin are presented in Table 6. Since our results are almost similar1 in the two multivariate frameworks, we refer to the results obtained by DCC-GARCH in the following tables. The mean of dynamic conditional correlation between BTC/SP500, BTC/FTSE100 and BTC/DAX30 were all positive. This finding indicates that our crypto currency did not act as a hedge for American, German and U.K stock index. The mean of the other dynamic conditional correlation pairs varied between -0.01074421 and -0.00044505. Among them, in panel A the mean dynamic conditional correlation coefficient of BTC/CNY was the largest at -0.00158053 and the minimum mean dynamic conditional correlation coefficient was BTC/JPY, which was -0.00044505. In panel B, the coefficient of BTC/HIS was the largest at -0.01074421, and the minimum coefficient was BTC/CAC40, which was - 0.00158689. This showed that Bitcoin could act as a hedge against their fluctuations.

Table 6: The dynamic conditional correlations between American dollar, stock index and BTC

Variables	The mean of dynamic conditional correlation
PANEL A	
BTC/JPY	-0.00044505
BTC/GBP	-0.00567043
BTC/EUR	-0.00324883
BTC/CNY	-0.00158053
PANEL B	
BTC/SP500	0.00012597
BTC/FTSE100	0.00438880
BTC/DAX30	0.00365595
BTC/CAC40	-0.00158689
BTC/HSI	-0.01074421

Note: These estimation results are based on the DCC model. For these convenient observations, the dynamic conditional correlation coefficients (ρ) are shown by means of arithmetic average.

The descriptive statistics of dynamic correlation coefficients (DCC) of each BTC-asset pairs are presented in Table 7. The statistics show that Bitcoin is 0.000778 positively correlated with DAX30 and on the other hand, it is slightly negatively correlated with all the other asset series. Nevertheless, the mean of the time-varying correlation coefficients for each pair is small, ranging only from mean -1.152154 to 0.000778, indicating that this crypto-currency can be used as a hedge in portfolios. T

Table 7: Summary statistics of conditional correlation estimated using a DCC-GARCH model

VARIABLES	MIN	MAX	MEAN	ST.DEV
Panel A				
BTC/JPY	-0.072223	0.083779	-0.000445	0.014736
BTC/GBP	-0.079340	0.019023	-0.005670	0.010929
BTC/EUR	-0.081673	0.105899	-0.003249	0.017733
BTC/CNY	-0.032101	0.168465	-0.001581	0.015056
Panel B				
BTC/SP500	-0.116920	0.087358	0.000126	0.008405
BTC/FTSE	-0.035031	0.202373	0.004389	0.006985
BTC/DAX30	0.000778	0.033337	0.003656	0.001611
BTC/CAC40	-0.011213	0.003085	-0.001587	0.001509
BTC/HSI	-1.152154	0.087793	-0.010744	0.027388

Note: This table shows the descriptive statistics of dynamic correlation coefficients (DCC) of each cryptocurrency- asset combinations.

V. Conclusion

Motivated by the Dyhrberg 2016 and Chen and Wang 2017 methodologies our objective was to examine variations in conditional correlations to determine when the Bitcoin acts as a hedge firstly against the American dollar and secondly against the stock markets using a univariate and a multivariate GARCH models. First of all, the GJR-GARCH model results for daily Bitcoin prices, exchange rates and stocks data during our sample period showed that: (1) BTC serves as a weak hedge for the stock market index changes in long term, with the exception of DAX30, during the period under study (2) BTC is a weak hedge against US dollar fluctuations in long term. Then, for the multivariate GARCH model results: (1) the mean of dynamic conditional correlation showed that the BTC can be considered as a diversifier more than a means of hedging against SP500, FTSE100 and DAX30 fluctuations and for all the other asset our crypto-hedging against SP500, FTSE100 and DAX30 fluctuations and for all the other asset our crypto-currency is regarded as a hedge in portfolios (2) the summary statistics of conditional correlations between the Ret_BTC and Ret_of each other series pair showed that this crypto-currency is a hedge against all financial assets changes except DAX30, confirming our first result (the univariate GARCH result). A noteworthy finding of our study is that Bitcoin is the digital gold and can be regarded like gold to eliminate or minimize specific market risks as a hedge highlighting its monetary asset role. Otherwise, it can be added in the variety of possible tools to market analysts to hedge market risks. Even more, Bitcoin creates a new opportunity for investors in terms of risk management, portfolio analysis and the stockholders sentiment in the financial market (Dyhrberg 2016). In light of these results, more researches should be done in order to uncover the financial aspect of this phenomenon.

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