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ORIGINAL ARTICLE

Relation Between Bitcoin and Its Forks: An Empirical Investigation

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Abstract
Cryptocurrencies are generating increasing interest with concerns about various economic and financial implications. Investors in cryptocurrencies are affected by the massive jumps and crashes in the market and it is of interest to portfolio managers to answer the following question: Does investing in Bitcoin and its forks offer diversification for investors? This paper aims to answer this question by examining the relationship between the returns of Bitcoin and the returns of its forks and their associated volatilities. Our sample covers the period between 2010 and 2017 and includes Bitcoin and the portfolio of its forks. Our results, based on Dynamic GARCH model, indicate that there is a positive relation between the returns of Bitcoin and the returns of its forks. In addition, the results also show a positive relation between the volatility of Bitcoin and its forks. Finally, we found both the news effect and memory effect are significant.

Keywords Cryptocurrency · Bitcoin · Forks · VAR

JEL Classification G11 · G12

Introduction

Financial markets have developed significantly overtime, and the financial instruments used have also evolved in line with the needs of the market. A recent development in the financial markets is the introduction of cryptocurrencies. The introduction of cryptocurrencies has reshaped the electronic payment system in a scale that was unspeakable just a few years ago. Currently, there are over 2000

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cryptocurrencies available on the internet with over $472 Billion of market capitalization.[1] Recently cryptocurrencies suffered fluctuations in their prices, crypto prices have dropped 70% from their all-time highs, resulting in periods of high volatility, and affecting wealth of many investors. Since cryptocurrency is mainly used as an asset rather than a currency, the cryptocurrency market is currently highly speculative, and more volatile and susceptible to speculative bubbles than other currencies. Cryptocurrency has, therefore, found a place in the financial markets and examining its volatility is of immense interest to investors and hence has implications on portfolio diversification.

There are over 17 million Bitcoins in circulation, Bitcoin's success has spawned several competing cryptocurrencies such as Ethereum, Litecoin, and Ripple. Any cryptocurrency can be divided into several forks. A fork is the term used in a single blockchain that deviates into two paths. This is usually due to a significant change in the protocol of the network, which effectively divides the blockchain into an old way of doing things and a new way to do things. Investors in cryptocurrencies span wide age bracket, which show interest among many investors. Whether investing in bitcoins and its forks is considered a hedge is one of the questions we answer in this paper, and which will be of great interest to investors and portfolio managers who invest in this market.

Our objective is to study the relation between the movement in Bitcoin and its forks and the dynamics of their volatilities controlling for S&P500, Euro-dollar exchange rate, interest rate, gold and their respective volatilities. Our result reveals a positive relation between Bitcoin returns and the return of the forks of Bitcoin. In addition, our GARCH results show a positive relation between forks and Bitcoin volatility. Finally, we found both the news effect and memory effect are significant.

The rest of the paper is organized as follows. In "Literature Review" section critically analyzes the literature, In "Data" section presents the data, in "Model and Research Methodology" section presents the methodology, in "Results" section discusses results, and "Conclusion" section concludes.

Literature Review

Bitcoin, launched in 2009 by an individual or group known under the pseudonym of Satoshi Nakamoto, is often regarded as the father of cryptocurrencies and all other cryptocurrencies are referred as the altcoins. Since its inception in 2009 as an open-source digital currency, Bitcoin has brought the attention of economists, policymakers, and traders. Importantly, it has inspired and provoked the release of many cryptocurrencies based on its technology—blockchain (Bouri et al. 2017). Bitcoin is unique because it does not rely on government/bank created money. In fact, the transactions occur directly between pseudonymous people (their real names are not known), meaning that there are no banks or intermediaries.

[1] https://coinmarketcap.com/currencies/bitcoin/

Cryptocurrency is a shared framework where exchanges happen without a focal player. Since cryptocurrency is an ongoing creation, there has been a moderate yet consistent increment in the measure of research work done in connection to this digital money. Yet the literature examining the financial implication of bitcoin is limited, as of our knowledge none is written on the relation between Bitcoins and its forks. The literature on the relation between Bitcoin prices, volatility and its forks is not abundant and this paper contributes to the literature.

According to cryptocurrency markets report about 55.20% of total market share belongs to Bitcoin,[2] while 11.94%, 9.34% and 2.58% shares are attributable to Ripple, Ethereum and Litecoin. Moreover, their report shows that 91.22% of cryptocurrency market involvers are males, while only 8.78% are females. The age distribution refers to ability of the cryptocurrency market to attract wide range of people from very young to very old. Interestingly, the share of elderly people (45+) is about 12.77%, which provides evidence for that cryptocurrency market attract from youngest to elderly people into financial activities.

Bitcoin Return

Bitcoin, the world's biggest computerized money, has risen by more than 1500% since the beginning of 2017. According to Katsiampa (2017), Bitcoin is the most popular cryptocurrency with a market share of more than 41%. Given its importance, significant amount of recent literature is dedicated to understanding the factors that affect the prices of Bitcoin. Ciaian et al. (2016), for example, examine the relationship between Bitcoin price and demand and supply fundamentals. They show that supply and demand of Bitcoin have strong impacts on its price and standard economic models can partly explain the fluctuation in its price. Li and Wang (2017) also maintain that Bitcoin prices adjust to economic fundamentals and market conditions. Urquhart (2017) complement these findings by documenting that Bitcoin's price and volume have a positive relationship. They show that Bitcoin volume can predict returns. In another related study, Polasik et al. (2015) state that an increase in the transaction volume lead to higher prices. Kjærland et al. (2018) also find that Google searches can significantly predict Bitcoin value. Ciaian et al. (2016) studied the relationship between Bitcoin price and demand and supply fundamentals, controlling for global economic factors (oil price and the Dow Jones index) and the desirability of Bitcoin to investors. They find that factors related to the risk and uncertainty of the Bitcoin system affect the behavior of Bitcoin.

In addition to demand and supply fundamentals, several researchers found technical factors like hashrate (measure of the mining difficulty) to be a positive driver of Bitcoin prices (Bouoiyour and Selmi 2015; Ciaian et al. 2016; Garcia et al. 2014; Georgoula et al. 2015; Hayes 2015; Kristoufek 2015). This strand of the literature argues that growth in the Blockchain network causes the hashrate to increase. When blockchain develops, the amount of generated mathematical operations also become

[2] https://coin.dance/stats.

more complex, thereby leading to higher hashrate. The higher the hashrate, the tougher the network security is. It is the for this reason that Bitcoin price is positively related to its hashrate. Furthermore, Liu and Tsyvinski (2021) find that cryptocurrency returns are determined by factors that are specific to cryptocurrency markets. They show that it is affected by cryptocurrency network factors, the number of wallet users, the number of active addresses, the number of transaction count, and the number of payment count. In a related study, Bouoiyour and Selmi (2015) argue that long-term fundamentals are likely to be major contributors to cryptocurrency price variations. They regressed Bitcoin price on investor's attractiveness, exchange trade volume, and hashrate. By doing so, they show the unpleasant speculative behavior of Bitcoin and provided insightful evidence that Bitcoin may be served partially for trade transactions.

Several other factors have also been identified as significant predictors of Bitcoin price. Zwick and Sarfaraz (2019), for example, document that gold is a significant indicator of Bitcoin prices. They show that this impact in not linear over the time. They find that, before October 2017, a significant negative and weak impact of gold on Bitcoin prices is found. This shows that investors see Bitcoin as a speculative asset than a hedge or safe haven. After October 2017, an increase in gold prices predicts a significant positive and strong impact on Bitcoin prices. They find that a rise in the demand for gold, traditionally motivated by economic or financial uncertainty, increases the demand for Bitcoin. Van Wijk (2013), for example, examine the impact of Dow Jones index on the value of Bitcoin. The show that Dow Jones index has a long-run and a short-run impact on the value of Bitcoin. Papadopoulos et al. (2017) and Vassiliadis et al. (2017) report strong correlation between Bitcoin and the contemporary stock market indices like NASDAQ, DAX and S&P500. They show that the correlation between Bitcoin and each of these indices remains above of 0.6 (normalized value) for lags up to 150 weeks. In another related study, Kjærland et al. (2018) find that S&P500 is a significant predictor of the returns of Bitcoin.

Georgoula et al. (2015) and Hayes (2015) find that the price of Bitcoin is negatively affected by the euro-dollar exchange rate. To the extent that this exchange rate represents the general level of prices, its inverse relationship with the value of Bitcoins contrasts the prediction of Fisher's equation associated with the quantity theory of money. Van Wijk (2013) also show that the euro-dollar exchange rate has a significant impact on the price of Bitcoin. Sapuric and Kokkinaki (2014) compare the Bitcoin exchange rate against six major global currencies. Their analysis indicates that Bitcoin has the highest accumulated volatility of percentage change in daily exchange rates. Dimitrova (2005) conclude that foreign investor may sell their financial assets after a decline in stock prices. This may lead to a depreciation of the respective currency, but may stimulate Bitcoin price, if investors substitute investment in stocks for investment in Bitcoin.

Corbet et al. (2018) examine the reaction of a broad set of digital assets to interest rates and quantitative easing announcements. They find a broad range of differing volatility responses and feedback dependent on the type of cryptocurrency investigated and as to whether the cryptocurrency was mineable or not. In another related study, Yermack (2013) finds Bitcoin prices to be considerably more volatile than gold prices. This result is interesting because, just like Bitcoin, gold is a natural

resource with limited supply. Dyhrberg (2016) highlight the diversifying potential of Bitcoin by showing that it can be used as a hedge against stocks and against the fluctuations in US dollar. Therefore, it was found to possess some of the same hedging abilities as gold and can be included in the variety of tools available to market analysts to hedge market-specific risk.

Bitcoin Volatility

The trading volume of Bitcoin has increased immensely since its conception. Although its popularity has grown worldwide, fluctuation of the prices is sometimes erratic. Phillip et al. (2018) employ the stochastic volatility model to examine the price volatility of several cryptocurrencies. They find that cryptocurrencies exhibit long memory, leverage, stochastic volatility and heavy tails. They also show that cryptocurrencies with lower market capitalizations exhibit larger variability. Gronwald (2014) show that Bitcoin prices are characterized by large price fluctuations, such as those found in newly emerging markets. This implies that returns of Bitcoin prices are characterized by both extreme movements and conditional heteroscedasticity. As this market is still in early stages, these results are generally to be expected. The volatility changes in Bitcoin were also studied by Bourie et al. (2016). Their analysis show that there exists an inverse relation between the stock market uncertainty and the Bitcoin volatility. This means that in an environment of high certainty in the stock market, market participants moved into Bitcoin to hedge any possible stock market losses. Their analysis shows a negative relation between the implied volatility index (VIX) and Bitcoin realized volatility. Moreover, Bourie et al. (2016) find that the volatility of Bitcoin decreases less as the price of Bitcoin increases, leading to an inverted asymmetry phenomenon. In another related study, Brière et al. (2015) claim that the volatility of Bitcoin prices is many times greater than that of stocks, bonds, hard currencies, and gold. They maintain that, due to lack of fundamental value and absence of regulation, Bitcoin possess different characteristics than many traditional assets. Davies (2014) finds that there is a relationship between the volatility of Bitcoin and two different measures of online search. Their findings, based on VAR and Granger causality, indicate that changes in Google Trends influence the realized volatility of Bitcoin. Changes in the volatility of Bitcoin also impact Google searches for Bitcoin. He implied that Google Trends could be a useful tool for forecasting future periods of volatility in the market for Bitcoin. Similarly, Ciaian et al. (2016) also find a positive relationship between Wikipedia searches and Bitcoin.

Bitcoin Forks

Any cryptocurrency can be divided into several forks. A fork is the term used in a single blockchain that deviates into two paths. This is usually due to a significant change in the protocol of the network, which effectively divides the blockchain into an old way of doing things and a new way to do things. Blockchain forks, which occur when two miners independently find and publish a new block referencing the

same previous block, occur regularly in permissionless blockchains, such as Bitcoin. More specifically, a blockchain fork occurs if two new blocks that reference the same previous block are independently found at the same time by different miners. Forks can also be the result of selfish mining, a mining strategy in which a miner withholds new blocks instead of immediately publishing them to gain an advantage in finding the next block. Although it often expresses of the Bitcoin log as a "chain" of blocks, in general the log could fork, perhaps at several points, leading to a structure that is more like a branching tree than a single linear sequence of blocks. There are many arguments, sometimes conflicting arguments, that would suggest that forks should affect the price of Bitcoin. For example, forks are thought to be dangerous to Bitcoin because they create multiple, competing versions of the transaction history and thus spread doubt about who owns which coins. However, fork may also give you access to "free" cryptocurrency. Therefore, it makes sense to keep hold of your cryptocurrency or even increase your stock of coin.

Data

The sample is composed of daily prices of Bitcoin and its 17 forks and covers the period between 2010 and 2017. The data are collected from www.coincheckup.com. The forks of Bitcoin include Litecoin, Bitcoin Cash, Dash, Bitcoin Gold, Zcash, Qtum, Decred, Digibyte, Syscoin, Navcoin, Peercoin, Bitcoin Diamond, Reddcoin, Elastos, Viacoin, Emercoin, and Groestlcoin. Each of the fork has a specific starting date. Therefore, the sample is constrained by the short length of the available time series. Our final sample period consists of the period in which data on all forks and Bitcoin are available. We use the forks to create a value-weighted portfolio of forks. The returns of Bitcoin (R_b) are computed as follows:

$$R_b = \log\left(\frac{P_{b,t}}{P_{b,t-1}}\right) \tag{1}$$

The returns of fork portfolio (Rp) are calculated as follows. In the following equation, w_i is the weight of fork i in the portfolio, and Ri is the return of fork i. The returns of each fork are computed in the same way as that of Bitcoin return.

$$R_p = \sum_{i=1}^{17} w_i * R_i \tag{2}$$

Table 1 shows descriptive statistics of daily returns in USD of the 17 forks of Bitcoin over the period 2010–2017. We observe that Dash has the highest mean, which indicates that it has the highest returns. It also has the highest standard deviation and the highest skewness.

Table 2 shows the correlation coefficient of the returns of the 17 forks and Bitcoin. There is a weak to moderate correlation between Bitcoin and its 17 forks, ranging from positive to negative correlation. The correlation between the different forks is a positive correlation.

Table 1 Summary statistics. Source: Author's estimates

Descriptive statistics (2010–2017)							
Forks		Mean	Variance	StD	CV	Skewness	Kurtosis
Litecoin	X1R	0.0043	0.0071	0.0846	19.5272	4.7472	64.8648
Bitcoin Cash	X2R	0.0025	0.0089	0.0943	37.5468	1.4142	7.2888
Dash	X3R	0.0575	2.0336	1.4260	24.8204	38.7571	1,571.4448
Bitcoin Gold	X4R	−0.0001	0.0099	0.0996	−677.1199	3.2914	32.8698
Zcash	X5R	−0.0004	0.0104	0.1021	−272.5606	3.6532	64.2702
Qtum	X6R	0.0273	0.3167	0.5628	20.5833	23.0872	558.1663
Decred	X7R	0.0185	0.1086	0.3295	17.7828	25.1299	730.4990
Digibyte	X8R	0.0092	0.0149	0.1222	13.2987	6.1133	86.0125
Syscoin	X9R	0.0079	0.0107	0.1033	13.0169	1.5981	7.8986
Navcoin	X10R	0.0108	0.0187	0.1366	12.6466	3.9014	40.8421
Peercoin	X11R	0.0016	0.0051	0.0717	45.3409	0.9191	8.3328
Bitcoin Diamond	X12R	0.0063	0.0565	0.2378	37.8209	7.5471	94.0706
Reddcoin	X13R	0.0169	0.1605	0.4006	23.6569	7.6533	109.6447
Elastos	X14R	−0.0052	0.0075	0.0869	−16.6783	0.8520	6.6946
Viacoin	X15R	0.0066	0.0139	0.1181	17.8099	3.1629	28.7042
Emercoin	X16R	0.0137	0.0423	0.2057	15.0104	9.8494	178.3472
Groestlcoin	X17R	0.0159	0.0367	0.1914	12.0377	4.7946	49.6500

Model and Research Methodology

In this paper, we use Vector Auto regression model to study the relationship between Bitcoin forks portfolio returns and Bitcoin returns. The conditional mean equation describing the returns of Bitcoin can be expressed as follows:

$$R_{b,t} = \alpha_i + \beta_{\text{dfx}}(DFX) + \beta_{\text{dr}}(\text{DR}) + \beta_{\text{dgold}}(\text{DGOLD}) + \beta_{\text{rsp}}(\text{RSP500}) + \sum_{j=1}^{n} \left(R_{p,t-j}\right) + \varepsilon_{b,t} \tag{3}$$

In the above equation, R_{bt} is Bitcoin return at time t, and ε_{bt} is the innovation to Bitcoin return equation. αi is the intercept of the Bitcoin equation and the Bitcoin forks equation. β_{jp_p} measure the response of Bitcoin returns to Bitcoin forks lags (where lags j=1 to n) respectively. The lag length is selected using the Akaike Information Criterion (AIC). The coefficients measure any causality between Bitcoin returns and Bitcoin forks' return, or the mean spillover between Bitcoin and Bitcoin forks returns. DR is interest rate, DFX is euro-dollar exchange rate, DGOLD is the return on gold, RSP500 is the return on S&P500 index.

We use a partial test (t-test). Our hypothesis is there is a positive relation between the return of Bitcoin Forks portfolio, and Bitcoin returns.

After modeling the conditional mean, we use GARCH to capture the joint volatility dynamics between Bitcoin returns and its forks returns.

Table 2 Correlation Matrix. Source: Author's estimates

Corr.	Correlation Matrix																	
	X1R	X2R	X3R	X4R	X5R	X6R	X7R	X8R	X9R	X10R	X11R	X12R	X13R	X14R	X15R	X16R	X17R	Bitcoin
X1R	1.000																	
X2R	0.411	1.000																
X3R	0.009	0.516	1.000															
X4R	0.429	0.620	0.433	1.000														
X5R	0.293	0.493	0.399	0.488	1.000													
X6R	0.193	0.254	0.127	0.349	0.154	1.000												
X7R	0.094	0.385	0.051	0.392	0.239	0.104	1.000											
X8R	0.198	0.392	0.049	0.367	0.193	0.091	0.076	1.000										
X9R	0.283	0.347	0.116	0.333	0.279	0.071	0.057	0.259	1.000									
X10R	0.200	0.282	0.063	0.292	0.249	0.088	0.075	0.198	0.184	1.000								
X11R	0.437	0.296	−0.013	0.314	0.262	0.114	0.076	0.200	0.263	0.172	1.000							
X12R	0.259	0.224	0.242	0.303	0.150	0.136	0.205	0.161	0.212	0.123	0.168	1.000						
X13R	0.003	0.123	0.013	0.076	0.010	−0.048	−0.013	0.064	0.039	0.017	0.023	0.061	1.000					
X14R	0.580	0.562	0.556	0.622	0.551	0.582	0.540	0.541	0.461	0.480	0.343	0.155	0.040	1.000				
X15R	0.239	0.357	0.021	0.327	0.267	0.100	0.083	0.218	0.238	0.190	0.213	0.208	0.031	0.449	1.000			
X16R	0.049	0.087	0.021	0.164	0.107	0.073	0.028	0.031	0.054	0.006	0.016	0.098	0.013	0.230	0.026	1.000		
X17R	0.128	0.213	−0.004	0.186	0.086	0.043	0.035	0.103	0.100	0.125	0.136	0.110	0.003	0.250	0.092	0.026	1.000	
Bitcoin	−0.002	−0.011	0.003	−0.022	0.024	−0.025	−0.013	−0.045	0.042	0.020	0.035	−0.016	0.047	−0.027	−0.004	−0.023	0.059	1.000

Table 3 VAR results

Dependent variable	Bitcoin
Variable	Coefficient
Constant	−0.706040 (0.015053)
FORKS	0.705277* (0.015399)
DFX	−0.403453** (0.201604)
DR	−0.061412 (0.054558)
DGOLD	−0.001597 (0.163470)
RSP500	−0.309172 (0.114211)
Observations	204
R-squared	0.815641
Adjusted *R*-squared	0.810985

(1) Parenthesis imply St. Error.

(2) *, ** indicate statistical significance at the 1, 5% levels respectively

The above regression was conducted using the following equation $R_{bt} = \alpha_i + \beta_{dfx}\text{DFX} + \beta_{dr}\text{DR} + \beta_{dgold}\text{DGOLD} + \beta_{rsp}\text{RSP500} + \sum_{j=1}^{n} \beta_{jp} R_{p_{t-j}} + \varepsilon_{bt}$

Let (σ_t^2) be variance

$$\left[\sigma_t^2\right] = [\sigma] + \left[a + bI_{t-1}\right] * \left[\varepsilon_{t-1}^2\right] + \left[d\sigma_{t-1}^2\right]$$
$$I_{t-1} = \begin{cases} 1, & \varepsilon_t < 0 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where σ is a constant, a captures the news effect on dynamic covariance. b is the leverage effect, bad news; bad news is when $\varepsilon t < 0$, d captures memory effect; the effect of past volatility on current volatility. We restrict the off-diagonal parameters to be zero. This specification has the advantage of dynamically estimating the variance without being subject to the curse of dimensionality.

Results

Results of Model 1: VAR

Table 3 presents our results. We start by testing the stationarity of each variable; we found that the following variables are not stationary; euro-dollar exchange rate, interest rate, and gold prices. We took the first difference to remedy this. We run a regression for Bitcoin and its forks, using four control variables: S&P 500, euro-dollar exchange rate, US interest rate and gold prices. Our results confirm our hypothesis of a positive relation between Bitcoin returns and its forks. Adjusted R-squared is 81.5% indicating that our model explains well the variation in of Bitcoin returns.

We conducted sensitivity checks by rerunning our model excluding control variables and focusing on forks and we found that 81% of the changes in Bitcoin is

explained by its forks, and the coefficient is 0.678 and this indicates a strong positive relation between Bitcoin and its Forks. Our results have implication on investor's diversification strategy and has implications on portfolio management and document a relation between Bitcoins returns and forks returns; a relationship that was not studied before in the literature.

Moreover, we examine the relation between the control variables and Bitcoin returns. Our results demonstrate that there is a negative relation between Bitcoin and the euro-dollar exchange rate and between Bitcoin and S&P500 at 5% significance. This means that any increase in the exchange rate or S&P500, will lead to a decrease in the returns of Bitcoin. This explains the surge in Bitcoins during the decline in the equity market during the latest pandemic. This finding is consistent with Van Wijk (2013) findings. Our results are also in line with Vassilladis et al. (2017) results, who found a strong cross-correlations between Bitcoin price with contemporary stock market indices like NASDAQ, DAX and S&P500. Moreover, this result is in line with Georgoula et al. (2015) and Hayes (2015). They found that the price of Bitcoin is negatively affected by the exchange rate between USD and Euro. To the extent that this exchange rate represents the general level of prices, its inverse relationship with the value of Bitcoin contrasts the prediction of Fisher's equation associated with the quantity theory of money. Finally, we found no relation between Bitcoin returns and both the interest rate and gold prices. Any increase or decrease in those variables have no effect on the returns of Bitcoin.

Results of Model 2: GARCH

The estimates of the GARCH equation are presented in Table 4. Our GARCH results show a positive relation between forks and Bitcoin volatility. In addition, we found both the news effect and past volatility effect to be significant. The leverage effect is significant indicating asymmetric effect of bad news versus good news. Moreover, past volatility effect on Bitcoin returns is significant. Our results are of interest to investors and portfolio managers; the two assets are positively correlated and hence they cannot be viewed as diversification alternatives.

Our results show that the interest rate has a significant effect on the volatility of Bitcoin, this is of significant implication given the recent hikes in interest rate. A subsequent paper will focus on the impact of recent hikes on the dynamic relation between Bitcoin and its Forks. Our results indicate that the Euro-dollar exchange rate, the S&P500, the volume of Bitcoin and the price of gold, have no significant effect on the volatility of Bitcoin.

Finally, we deduct from the VAR and GARCH results that Forks' returns, and volatility affects Bitcoins movements and their respective volatility, one implication on portfolio management is that these two assets are poor hedge to each other and provide meager diversification for any investor. On the contrary investing in the stock market proxied by S&P 500 provides is a good hedge and likewise is investing in foreign exchange market. An interesting result on the relation between interest rate and Bitcoins volatility, while interest rate does not affect the returns of Bitcoins,

Table 4 GARCH results

Variance	
Variable	Coefficient
Constant	−0.000337 (0.000195)
RESID(−1)^2	0.151226 (0.087003)
RESID(-1)^2*(RESID(−1)<0)	0.484586** (0.225977)
GARCH(−1)	0.484951* (0.118066)
FORKS	0.000394** (0.000203)
DFX	−0.002538 (0.003217)
DR	0.002451** (0.001197)
DGOLD	−0.002357 (0.002634)
RSP500	−0.002196 (0.002191)
Observations	204
R-squared	0.815641
Adjusted *R*-squared	0.810985

(1) Parenthesis imply St. Error.

(2) *, ** indicate statistical significance at the 1%, 5% levels respectively

The above regression was conducted using the following equation $\left[\left(\sigma_t^2\right)\right] = [\sigma] + \left[a + bI_{t-1}\right] * \left[\varepsilon_{t-1}^2\right] + \left[d\sigma_{t-1}^2\right]$

yet its volatility does. This also has implication on portfolio management, where in period of uncertainty and high volatility of interest rate investing in Bitcoins is not recommended.

Conclusion

The cryptocurrency market is growing since its inception in 2009 and the literature on this market is racing to keep with its innovation. There is still ambiguity concerning many aspects related to cryptocurrencies and their relationship with the financial system and various macroeconomic variables.

Cryptocurrency has become a global term; still not fully understood by most of the people, banks, governments, and many companies. Opposite to the financial assets, they do not have intrinsic value. There are over 2000 cryptocurrencies available on internet. Bitcoin often is regarded as father of cryptocurrencies, the first decentralized cryptocurrency, has gained a large interest from the media, academics, and the finance industry since its inception in 2009. One of the subtopics of Blockchain is Forks, that we study in this paper.

Our paper examines the relation between Bitcoin and its forks and their volatility interactions. The results of our study confirmed that there is a strong positive relation between Bitcoin returns and forks returns, these results have an important implication on investors' diversification strategy. Our results show a negative relation between Bitcoin returns and S&P500, and a negative relation between Bitcoin return and exchange rate. In addition, our results indicate that understanding the

movement in Bitcoin forks helps understanding the movement in Bitcoins and hence could be used in predicting Bitcoin returns. Our GARCH results show a positive relation between forks and Bitcoin volatility. In addition, we found both the news effect and past volatility effect are significant. Finally, we found that memory effect is significant indicating that past volatility effect on Bitcoin returns is significant.

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