**Are CBOE Bitcoin Futures a Safe-Haven?**

1. **Introduction**

Since the launch of Bitcoin futures by the Chicago Board of Exchange in December 2017, the relationship between Bitcoin and Bitcoin futures has not been explored to a large extent in the academic literature. While these are not the first derivatives of Bitcoin, as there have been prediction markets present for some time, the novelty to the CBOE Bitcoin Futures relies on the respectability of the exchange as a financial institution which provides a more legitimized means of investing in Bitcoin. Transacting in Bitcoin has a large counterparty risk and a liquidity problem. Aware of these issues, investors will likely find the new futures market more attractive than buying and selling Bitcoin directly as the futures settle in USD, have a unified reference price of Bitcoin, are regulated by the Commodity Futures Trading Commission, and allow for the ability to short the asset. Further, as many recent studies find that Bitcoin may act as a safe-haven from shocks in the stock market, portfolio managers may seek to use Bitcoin futures to reduce their portfolio risk. Thus, do Bitcoin futures provide the same safe-haven effect as described in the literature, and what is the relationship between Bitcoin futures returns and their volatility?

This paper reviews several groups of literature on Bitcoin. The first group of papers introduces Bitcoin as a technology, presents a few studies on the risks inherent in the use of Bitcoin, and describes how Bitcoin is a speculative investment. The second group of papers discusses the use of traditional commodities and Bitcoin as a safe-haven.

1. **A Background on Bitcoin**

Bitcoin is a decentralized virtual currency that boasts a new technology called blockchain which, put simply, is a shared public ledger of all confirmed transactions of Bitcoin. To confirm these transactions and transact in Bitcoin, the technology relies on a distributed consensus system otherwise called “mining”which validates the transaction through a network of computers. These computers evaluate increasingly difficult cryptographic hash functions to find a specific chain of randomly generated alphanumeric characters. Once found, the correct alphanumeric string of characters symbolizes a block being added to the block chain and the transaction being validated. Participating miners are incentivized to validate transactions because the computer that ascertains the correct string of characters receives a reward of newly generated Bitcoin which in January 2018 was 12.5 Bitcoin per block representing $200,000 of US currency at that time. (“How Bitcoin Works”). However, the number of Bitcoin rewarded per block decreases with time as the model allowing the generation of the currency asymptotically reduces the amount of newly minted Bitcoin to zero as the total number of Bitcoin in the market approaches 21 million (Nakamoto 2018).

Given this new technology, Yermack (2013) critiques the efficacy of Bitcoin as a currency. He analyzes Bitcoin on several factors that influence currency: if it functions as a medium of exchange, a unit of account, and a store of value. According to Yermack 2013, Bitcoin has several glaring issues for satisfying these criteria. For one, it is considerably more difficult to procure Bitcoin compared to other currencies. Exchanges of Bitcoin have low liquidity and significant bid-ask spreads. Secondly, Bitcoin cannot be deposited in banks and must be stored in an electronic wallet on a computer. The storage of value is contingent on the accurate storage of the Bitcoin wallet and has inherent risks. Lastly, he argues that Bitcoin has no commercial value or practical use due to the small volume of transactions that take place in Bitcoin. He pushes that Bitcoin is more of a speculative investment than an actual currency (Yermack 2013).

Like Yermack (2013), Moore (2013) discusses risks associated with transacting in Bitcoin acquired through Bitcoin exchanges. His analysis focuses on the survivability of Bitcoin exchanges. Interestingly, he finds that of the 40 Bitcoin exchanges that have existed up to 2013, 18 exchanges have closed and 5 of these exchanges did not reimburse the participants which further suggests that there are real risks of transacting in Bitcoin (Moore 2013).

Foley, Karlsen, & Putniii (2018) utilize the public ledger of Bitcoin transactions to decipher what Bitcoin wallet accounts are likely to be linked to criminal activity based on their transactional history. In their study, they categorize Bitcoin users into two different bins illegal users and legal users such as speculative traders. They find that “Illegal users are estimated to control around 38.21% of Bitcoin addresses and account for one-fifth (20.3%) of the dollar volume of Bitcoin transactions. In dollar terms, illegal users conduct approximately $378 billion worth of Bitcoin transactions.” Essentially, illegal users control a sizable portion of Bitcoin transactions which constitutes a practical use for Bitcoin and a commercial value. This notion differs from the perspective of Yermack (2013). Also, Foley, Karlsen, & Putniii (2018) find that the amount of illegal activity varies over time which is suggested to be related to the closure of darknet market places like the SilkRoad, a market place for illicit drugs and services. Further, the rise of media coverage and interest in Bitcoin seem to cause a decline in illicit trade. “The proportion of illegal activity in Bitcoin is inversely related to the Google search intensity of the keyword Bitcoin” (Foley, Karlsen, & Putniii 2018). This follows a similar notion that Kristoufek (2013) explores where Google searches for the word Bitcoin are postulated to be related to speculative trading and influence the price of Bitcoin.

Kristoufek (2013) argues that Bitcoin does not have a commercial value or practical use and that investor sentiment should be the major driver of the price as the only strategy is to buy and hold in the Bitcoin market. The assumption made is that investor sentiment can be measured by internet searches for the word *Bitcoin.* Through estimating a VAR model, it is found that Google searches cause Bitcoin prices in a bi-directional manner. Moreover, looking at both the bull and bear market situations, he shows that the interest in Bitcoin as measured by Google searches for the word Bitcoin increases the volatility of the price (Kristoufek 2013).

1. **The Safe-Haven Attribute and Asymmetric Volatility**

In the breadth of literature on Bitcoin volatility and its hedging capability, the notion of a safe-haven effect comparable to that of gold and other commodities is suggested to explain why Bitcoin volatility appears to be inversely related with the volatility of equities. The following studies introduce how a commodity can be a safe-haven or a hedge and how Bitcoin is proposed to be a safe-haven.

Gold is considered a traditional commodity that has been largely viewed as a safe-haven from equity shocks but Baur and Lucey (2009) explicitly validate this assertion. They define three categories of financial instruments: a hedge, a diversifier, and a safe-haven asset. A hedge is an asset that is uncorrelated or negatively correlated with another asset or portfolio on average. A diversifier is defined as an asset that is positively but not perfectly correlated with another asset or portfolio on average. A safe-haven is defined as an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil. To test whether gold is considered a part of one of these categories, they construct a linear regression outlined in equation (1) where the authors estimate the impact stock returns and bond returns have on gold returns with indicator variables *rstock, t(q)*  and *rbond, t(q)*.

 (1)

The indicator variables are one when the returns of the stock or bond are lower than 1%, 2.5% or 5% quantile. The indicators seek to distinguish when the stock and bond markets are in times of stress or extreme market conditions. For data, daily MSCI stock and bond returns and the U.S. closing spot gold returns are used. They assume that gold does not influence stock or bond prices and that the relationship between gold and equities and bond market changes dynamically over time. To allow for variation across time, the authors build a conditional variance estimation to model the error term et. Ultimately, Baur and Lucey (2009) find that gold can be a safe-haven for equities but only for 15 days after an extreme market downswing.

Bour (2012) studies the asymmetric volatility in the gold market to further analyze if gold adequately acts as a safe-haven in times of turmoil. Asymmetric volatility models typically measure how volatility changes with respect to positive or negative innovations in the first moment. In the context of equities, these models evaluate how the volatility for the returns of a stock change when the return is negative or positive – essentially measuring the effect of bad news and good news on volatility. In the literature, the presence of volatility asymmetry for equities is well documented, and many authors find that volatility increases as negative returns increase. Several explanations are given for this phenomenon: one is coined the leverage effect and the second is called volatility feedback effect. Black (1976) explains the leverage effect as when a firm realizes a decrease in its stock price, its capital structure changes and volatility increases. Campbell (1992) conjectures that when information from any major news, good or bad, disseminates into the market, volatility increases and when volatility increases, the price of the stock decreases. Understanding this, Bour (2012) models an asymmetric GARCH model to see how gold behaves in the asymmetric return-volatility relationship observed in the equities markets. Bour finds that there is an inverted asymmetric relationship between gold returns and volatility which asserts that when gold returns are low, volatility is low and when gold returns are high, volatility is high.

In the equity space, Depken (2001) leans on prior research to model the volatility of stocks using volume data. He analyzes the effect of good and bad news on explaining the volatility of 10 recently split stock return series. Using a novel method to decompose volume data into a positive and negative feedback signals, he explores if there is an asymmetric relationship between these signals and finds that they have more explanatory power than simply using volume data. Depken (2001) conjectures that younger stocks react asymmetrically to good news and older more established stocks react symmetrically.

As Bitcoin has recently been declared a commodity by the Chicago Board of Exchange, several recent papersexamine the safe-haven effect and ability of Bitcoin to hedge market volatility. Bouri & Azzi (2016) focus on how the relationship between Bitcoin returns and the volatility of Bitcoin has changed after the large Bitcoin price crash in 2013. To estimate this relationship, they use an asymmetric GARCH model that measures the volatility in Bitcoin prices and how the volatility changes with the direction of shocks to the series. Estimation for this model relies on the maximum likelihood method. After finding that there is no statistical evidence that either direction of shocks has a larger magnitude over the other, they break the series into two pieces: before and after the price shock of 2013. According to their model, the return-volatility asymmetry coefficient is negative before 2013 and not statistically significant after 2013. To interpret this, Bouri & Azzi (2016**)** state: “If Bitcoin prices increase in periods of economic/financial turmoil, during which stock markets fall, investors purchase Bitcoin and transmit the increased uncertainty and volatility of the stock markets to the Bitcoin market.” To compare to equities, the same methods are employed to find the return-volatility relationship in the S&P 500 index. Showing that the asymmetric return-volatility relationship is positive and statistically significant, they indicate that negative return shocks tend to signal stronger volatility which is the opposite of Bitcoin’s relationship. Further, with the information regarding Bitcoin’s return-volatility relationship to the S&P500 index, a portfolio is constructed of Bitcoin and the index is calculated. Ultimately, the portfolio achieves a lower risk for the same return with the addition of Bitcoin (Bouri 2016).

Like Bouri (2016), this study conducts an analysis on the return-volatility relationship in Bitcoin futures and compares the Bitcoin futures returns volatility to the US equities volatility index.

1. **Data**

In this section, the data used in this study is described. Analyses are broken into several times series to highlight the changing nature that Bouri (2016) had observed in safe-haven effects for Bitcoin. The total series is from December 12th, 2017 to September 14th, 2018 for a total of 191 observations. This is broken into a smaller subset to compare a time of turmoil to a more stable market environment. The time of turmoil is December 12th, 2017 to March 9th, 2018 where most of the Bitcoin futures and stock market variability occur. The data from March 9th, 2018 to September 14th, 2018 show signs of less extreme swings and I will refer to this time frame as the normal market condition.

Bitcoin futures prices were obtained from daily closing prices listed on the CBOE website for each monthly Bitcoin future contract. These prices represent the closing price as of 4:00pm EST and are only published on weekdays during market hours. As the futures settle monthly, a price index is constructed to represent a continuous price of the futures by taking the price of the contract closest to the most recent settlement date. The futures contracts are linked to the underlying price of Bitcoin as determined in the Gemni exchange.

The S&P 500 index, CBOE VIX, and SPDR GOLD ETF data were obtained from Yahoo finance’s API. Yahoo provides closing, open, high and low prices for each as well as volume data. Both the S&P 500 and SPDR are differenced to create daily returns.

Google search trends for the word Bitcoin are taken from Google’s explore website. The data are reported as the number of searches of the word “Bitcoin” per day. However, Google normalizes the data to represent the highest daily searches in a selected time frame to be 100 and does not give the raw number of searches per day but a representation of it.

1. **Methods**

As Baur (2012) had used Glosten, Jaganathan, and Runkle [1993]’s asymmetric GARCH model to investigate the impact of positive and negative returns of gold on its volatility, this study attempts to use the same model to evaluate Bitcoin futures returns to its volatility. Explicitly, the model is described below.

**Model 1 - Asymmetric GARCH Model**

The first moment of the model estimates a mean return. The second moment of the model incorporates the lagged squared error term as an indication of positive swings in the return of Bitcoin futures, - this models volatility independently when returns are negative and positive If is positive, then positive shocks to the Bitcoin futures returns increase volatility.

Additionally, employing another approach to asymmetrically model positive and negative feedback, Depken (2001) uses the close price and high price to break out volume data in stocks to determine if good news asymmetrically impacts a stock. Incorporating this into my study yields the introduction of two new variables: good news and bad news volume or GNV and BNV defined below where Volumet is from any return series Xt.

Model 2 is applied to Bitcoin futures, SPDR Gold ETF, and to the S&P 500 for reference. These results are listed in Table 3.

**Model 2 - Asymmetric GARCH Model with Good News and Bad News Volume**

Further, if a safe-haven commodity acts as Bouri & Azzi (2016**)** suggest where investors in downturn transmit volatility from the stock market to the Bitcoin market, then a safe-haven commodity’s volatility would have a negative correlation to the stock market volatility. Thus, an estimate for Bitcoin futures returns’ conditional volatility is created and compared to the US VIX as a proxy for S&P 500 volatility. The conditional volatility for Bitcoin futures returns are modeled through the below GARCH structure to incorporate the US VIX in explaining Bitcoin futures volatility and the results are shown in . If is found to be statistically significant then the conditional variance of Bitcoin futures returns must be a function of the US volatility index and therefore the two markets are linked in their conditional variances. Moreover, if is negative, then the conditional variance of Bitcoin futures returns decreases with as the volatility increases in the stock market. Meaning, that when price change volatility increases in equities market, Bitcoin future returns become less volatile and may act like a safe-haven for equity shocks.

***Model 3 - Augmented GARCH Model VIX***

As Kristoufek (2013) asserts that Bitcoin is a speculative asset and finds that Google searches for the word Bitcoin appear to be a proxy for this. Bitcoin futures may also be a speculative asset which in time of turmoil, pure interest may increase the volatility of the underlying asset more so than the volume of Bitcoin futures can explain. Further, if Bitcoin futures are truly a safe-haven to the US stock markets then speculation on Bitcoin should not affect the relationship between Bitcoin futures volatility and the US VIX.

**Model 4 - Augmented GARCH Model with Speculative Investment Proxy**

1. **Results**

Prior researchers find that gold and Bitcoin under certain conditions have an asymmetric volatility in their returns such that when returns are positive, volatility increases. Authors attribute this effect to a commodity acting as a safe-haven where stock market turmoil volatility is transmitted to the commodity markets. Several models are estimated to find a similar phenomenon in Bitcoin futures returns and the results are discussed in this section.

Employing Model 1, the asymmetric volatility parameter, a7, is statistically significant and positive; indicating that under normal market conditions, positive returns indicate more volatility like the relationship found in Bour (2012). However, the relationship does not hold for the entire sample as the full sample a7 is not statistically significant. Results for model 1 are shown in Table 2.

Incorporating good news and bad news volume data as Depken (2001) does in his paper yields that volume associated with good news is positive but not statistically different from bad news volume for the full dataset. Again, reinforcing that there is not an asymmetry for the commodity. Interestingly, the Gold ETF index return series, SPDR, also exhibits similar characteristics as Bitcoin future returns under the same framework as model 2. Gold returns do not show signs of asymmetry where good and bad news volumes are not statistically different from each other. During this time, the S&P 500 index does show signs of an asymmetry in its second moment. Good news volume decreases volatility and is statistically different than bad news which is estimated to increase. Results are shown in Table 3 for all three models.

In model 3, I relate the VIX to the volatility of the Bitcoin future market to implicitly relate market volatility to Bitcoin future volatility. The results suggest that there is a negative relationship between Bitcoin futures return volatility and the US VIX during the turmoil dataset, from December 12th, 2017 to March 9th, 2018. Charts 1 & 2 make this notion clear that there appears to be a negative correlation between VIX and Bitcoin futures return volatility. Chart 1 shows the volatility of Bitcoin futures returns over time as modeled by a GARCH (1,1) process and Chart 2 depicts the VIX over time. Meaning, as market volatility increases, Bitcoin future volatility decreases. Yet, the negative correlation does not maintain throughout the sample as in normal market conditions, the VIX parameter, a6, flips and is estimated to positive. Does this mean Bitcoin futures become more stable in a VIX turmoil?

As Kristoufek (2013) and Yermack (2013) argue that Bitcoin is a speculative investment, could it be that the Bitcoin futures market merely had a conveniently timed bubble that coincided with large swing in the fix? To test this hypothesis, I estimate model 4 which jointly estimates the effect of the following variables on Bitcoin futures volatility: good and bad news volume; the VIX; and a proxy for a speculative investment, google trends data. Controlling for hype around Bitcoin, I find that google trends data primarily explains the volatility of Bitcoin futures returns. This gives reason to believe that this is not a safe-haven asset and more akin to a speculative investment asset.

1. **Conclusion and Further Research**

In conclusion, there is some evidence to suggest that Bitcoin futures act as a safe-haven through their volatility relationship to the VIX. However, these results are not proven to be robust against the assertion that Bitcoin and the surrounding financial products are merely speculative investments. Further research should also consider how the relationship between well-known safe-haven assets to the VIX and how this compares to Bitcoin futures. In addition, a test should be conducted where Bitcoin futures are added to a portfolio of the S&P 500 and benchmarked against well-known safe-haven assets.

**Bibliography**

Baur, D. G., & Lucey, B. M. (2009). Is Gold a Hedge or a Safe-haven? an Analysis of Stocks,

Bonds and Gold. SSRN Electronic Journal. doi:10.2139/ssrn.952289

Baur, D. (2012). Asymmetric volatility in the gold market. Journal of Alternative Investments

14(4): 26–38.

Black, Fischer, (1976), Studies of stock price volatility changes, Proceedings of the 1976

Meetings of the American Statistical Association, Business and Economics Statistics

Section, pp. 177-181.

Bouri, E., & Azzi, G. (2016). On the Return-Volatility Relationship in the Bitcoin Market around

the Price Crash of 2013. SSRN Electronic Journal. doi:10.2139/ssrn.2869855

Bouri, E., Gupta, R., Tiwari, A., & Roubaud, D. (2017). Does Bitcoin hedge global uncertainty?

Evidence from wavelet-based quantile-in-quantile regressions. Finance Research Letters,

23, 87–95. doi:10.1016/j.frl.2017.02.009

Depken, C. A. (2016). Good news, bad news and GARCH effects in stock return data. Journal of

Applied Economics, iv(2), 313–327. Retrieved from

http://search.proquest.com/docview/39136567/

Foley, S. M., Karlsen, J. R., & Putniii, T. J. (2018). Sex, Drugs, and Bitcoin: How Much Illegal

Activity Is Financed Through Cryptocurrencies? SSRN Electronic Journal.

Hentschel, L., & Campbell, J. (1992). No News is Good News: An Asymmetric Model of

Changing Volatility in Stock Returns, 31(3).

"How Bitcoin mining works." CoinDesk. January 31, 2018. Accessed March 11, 2018.

https://www.coindesk.com/information/how-Bitcoin-mining-works/.

Kristoufek, L. (2013). Bitcoin meets Google Trends and Wikipedia: Quantifying the relationship

between phenomena of the Internet era. Scientific Reports, 3, 3415. URL:

Http://www.nature.com/articles/srep03415

Glosten, L., Jagannathan, R., & Runkle, D. (1993). On the Relation between the Expected Value

and the Volatility of the Nominal Excess Return on Stocks. The Journal of Finance,

48(5), 1779-1801.

Moore, T., & Christin, N. (2013). Beware the Middleman: Empirical Analysis of Bitcoin-

Exchange Risk. Financial Cryptography and Data Security Lecture Notes in Computer

Science, 25-35. doi:10.1007/978-3-642-39884-1\_3

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system, Unpublished manuscript.

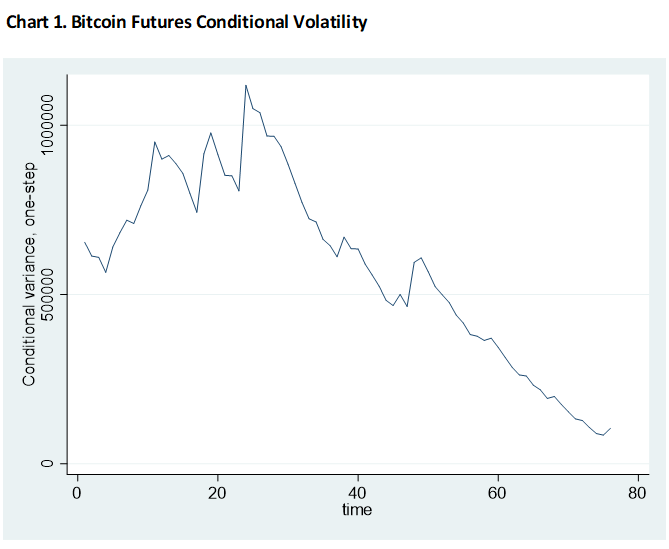
41 Noether, S., 2015, Ring signature confidential transactions for monero, In IACR

Cryptology ePrint Archive, 1098.

Yermack, D. (2013). Is Bitcoin a real currency? An economic appraisal. (No. w19747). National

Bureau of Economic Research. URL: http://www.nber.org/papers/w19747

**Appendix**



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| **Chart 2.** | | |  |  |  |  |
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| **Table 1. Data Summary** |  |  |  |  |  |  |



**Table 2. Bitcoin Future Returns Models**



**Table 3. Reference Models**

