Are CBOE Bitcoin Futures a Safe-Haven?

I. Introduction

~~With~~ the launch of the Chicago Board of Exchange's Bitcoin futures 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. ~~As will be discussed,~~ 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 cash, 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 ~~have found~~ 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 and their futures?

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.

II. A Background on Bitcoin

~~What is 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 was 12.5 Bitcoin per block representing $200,000 of US currency ("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 as 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 the exchanges did not reimburse the participants, which further suggests that there are real risks of transacting in Bitcoin (Moore 2013).

Foley (2018) utilizes 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 (2018) finds 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 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).

III. The Safe-Haven Attribute of Traditional and Untraditional Commodities

How do you know this is true?

Given the insight into the Bitcoin market place, any shocks to Bitcoin should be theoretically uncorrelated to stock market fluctuations being that returns appear to be driven by internet searches which may be a useful property for portfolio managers in risk mitigation. 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 ~~as measured in various forms~~. 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 to various equities.

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 $r_{stock,\ t(q)}$ and $r_{stock,\ t(q)}$.

$$r_{gold,t} = a + b_1 r_{stock,t} + b_2 r_{stock,t(q)} + c_1 r_{bond,t} + c_2 r_{bond,t(q)} + e_t \quad (1)$$

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 e_t. 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 increase. Campbell (1992) conjectures that when any major news, good or bad, breaks on the market volatility increases and when volatility increases the price of the stock decrease. 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.

As Bitcoin has recently been declared a commodity, several recent papers examine the safe-haven effect and ability of Bitcoin to hedge market volatility. Corbet (2017) analyzes the return and volatility transfer across three major crypto currencies and other financial assets such as gold, bonds, equities, and the global volatility index. He finds that cryptocurrencies are unrelated to market shocks and can be an effective tool in risk management. Several methods are employed to reach this conclusion. The author utilizes a generalized variance decomposition as used in Diebold (2012) which measures the direction and intensity of spillovers effects across markets through several metrics such as Total Spillover Index and Net Spillover Index. To measure intensity, a unique metric introduced by Diebold called the Total Spillover index estimates the volatility spillover from market to market. Another metric introduced by Diebold to analyze the direction of the spillover effect is the Net Spillover Index which measures the total shocks transmitted from any market to the receiving market minus the shocks transmitted back from the receiving market to the original market. Second, a multivariate GARCH model is further used for robustness because the volatility of returns across markets vary over time. He uses a DCC-MVGARCH model to analyze the relationships between the different cryptocurrencies considering structural breaks due to large-scale hackings of exchanges like the hacking of MT. GOX, the closure of the Silk Road, Ultimately, they find that the cryptocurrencies are interconnected and that "our research has indicated there is a role for cryptocurrencies in an investor portfolio but that their structure and behavior also indicate the cryptocurrency market contains its own idiosyncratic risks that are difficult to hedge against." (Corbet 2017)

Bouri & Azzi (2016) perform a similar study, however, they 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 one, the volatility in Bitcoin prices and two, 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 Corbet (2017) and 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.

IV. Data

In this section, the data series used in this study are described. All series are observations of daily closing prices from December 12th 2017 to May 2nd 2018 for a total of 97 observations and have been differenced. Summary statistics and a correlation matrix are represented in Table 1 and Table 2 in the appendix, respectively.

Bitcoin futures prices are taken from daily historical 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.

As used by other authors, Bitcoin closing prices come from CoinDesk, an index for the price of Bitcoin. It tracks a simple average of the four major Bitcoin exchanges: Bitstamp, Coinbase, itBit, and Bitfinex.

The S&P 500 index close price is taken from Yahoo! finance's API and differenced to represent daily returns. Similarly, the US VIX daily closing values are also taken from Yahoo! finance's API.

Google search trends for the word Bitcoin are taken from Google's explore website. The data are normalized to represent the percentage to the highest searched day. This series is differenced to represent the change in daily searches.

Gold returns are proxied by the SPDR gold shares ETF returns. Shares of this ETF represent a fractional, undivided interest in gold bullion held by the SPDR Gold Trust.

V. Methods

Following previous

~~As prior~~ authors ~~have used~~, this study models an asymmetric GARCH model to evaluate the relationship between the returns of Bitcoin Futures and their volatility.

Asymmetric GARCH Model

$$FuturesReturns = b_0 + b_1(GoldReturns) + b_2(S\&P500\ Returns) + b_3(\Delta GoogTrends) + e_t$$

$$\sigma_t^2 = \gamma_0 + a_1 e_{t-1}^2 + a_2 e_{t-1}^2 I(e_{t-1} > 0) + a_3 \sigma_{t-1}^2$$

The first moment of the model includes gold returns, S&P 500 returns, and the change in google trends to explain Bitcoin returns. The inclusion of gold returns and the S&P 500 returns mirrors Bouri (2016) for modeling Bitcoin returns. Also, Bitcoin futures returns may be related to investor sentiment as Kristoufek (2013) had found in his study of Bitcoin. The second moment of the model incorporates the lagged squared error term as an indication of positive or negative swings in the return of Bitcoin futures, a_2. This models volatility when returns are negative and positive. If a_2 is positive, then positive shocks to the Bitcoin futures returns increase volatility. *Currently, this model has not been estimated and will need to be researched more extensively in fall 2018.*

~~Given~~ If the asymmetric model does not converge in its maximum likelihood estimation, there may be a simpler way of determining if Bitcoin futures are really a safe-haven. If a safe-haven commodity acts as Bouri & Azzi (2016) suggest where investors in a 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. Thus, an estimate for Bitcoin Futures returns' conditional volatility is created and compared to the US VIX as a proxy for US stocks

volatility. The conditional volatility for Bitcoin futures returns are modeled through the below GARCH structure. Results are listed in Table 3 in the appendix.

Bitcoin Futures Return GARCH(1,1)

$$FuturesReturns = b_0 + b_1(FuturesReturns_{t-1}) + e_t$$
$$\sigma_t^2 = \gamma_0 + a_1 e_{t-1}^2 + a_2 \sigma_{t-1}^2$$

To further investigate, an augmented GARCH is modeled to incorporate the US VIX in explaining Bitcoin futures volatility and the results are shown in Table 5. If a_3 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 a_3 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 returns become less volatile and may act like a safe-haven for equity shocks.

Augmented GARCH Model

$$FuturesReturns = b_0 + b_1(FuturesReturns_{t-1}) + e_t$$
$$\sigma_t^2 = \gamma_0 + a_1 e_{t-1}^2 + a_2 \sigma_{t-1}^2 + a_3(US\ VIX)$$

VI. Results

In general, the results suggest that there is a negative relationship between Bitcoin futures return volatility and the US VIX. Charts 1 & 2 make this notion clear. Chart 1 shows the models volatility of Bitcoin futures returns over time. Chart 2 depicts the VIX over time. Looking at both charts there appears to be a correlation between them.

When including the VIX in modeling Bitcoin futures volatility, the parameter a_3 in the Augmented GARCH model is found to be statistically significant at less than the 1% confidence level as indicated by the p-value in Table 5. Further, the coefficient is found to be negative. Thus, Bitcoin futures return volatility appears to be negatively related with the volatility of US equities.

VII. 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 and in future research this will be investigated. 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.

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Appendix

Table 1. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Future Returns	97	-97.06	745.26	-2745	1850
Bitcoin Returns	97	-77.11	736.52	-2464.69	1888.12
S&P 500 Returns	97	-0.25	30.10	-113.19	70.29
ΔGoogle Trends	97	-0.57	9.31	-60	48
US VIX	97	16.41	5.72	9.01	37.32

Table 2. Correlation Matrix

Variable	Future Returns	Bitcoin Returns	S&P 500 Returns	ΔGoogle Trends	US VIX
Future Returns	1				
Bitcoin Returns	0.894	1			
S&P 500 Returns	0.134	0.132	1		
ΔGoogle Trends	-0.385	-0.401	0.027	1	
US VIX	0.185	0.162	-0.022	-0.011	1

Table 3. Bitcoin Futures Conditional Variance Model Estimates

Parameter	Estimate	Std Error	z-value	p-value
b_0	-8.81	52.58	-0.17	0.87
b_1	-0.05	0.10	-0.53	0.60
y_0	-2,895.93	4,252.06	-0.68	0.50
a_1	0.07	0.04	1.75	0.08
a_2	0.92	0.03	26.99	0.00

Note: Variances calcualted with White robust errors

Table 4. Bitcoin Conditional Variance Model Estimates

Parameter	Estimate	Std Error	z-value	p-value
b_0	-19.87	54.59	-0.36	0.72
b_1	-0.14	0.11	-1.27	0.21
y_0	1,236.71	7,076.37	0.17	0.86
a_1	0.06	0.04	1.57	0.12
a_2	0.92	0.04	24.08	0.00

Note: Variances calcualted with White robust errors

Table 6. Bitcoin Futures Augmented GARCH(1,1) Model

Parameter	Estimate	Std Error	z-value	p-value
b_0	-14.91	66.94	-0.22	0.82
b_1	-0.04	0.10	-0.36	0.72
y_0	14.35	0.71	20.09	0.00
a_1	0.13	0.10	1.31	0.19
a_2	0.46	0.18	2.53	0.01
a_3	-0.14	0.04	-3.47	0.00

Note: Variances calcualted with White robust errors

Chart 1. Bitcoin Futures Conditional Volatility

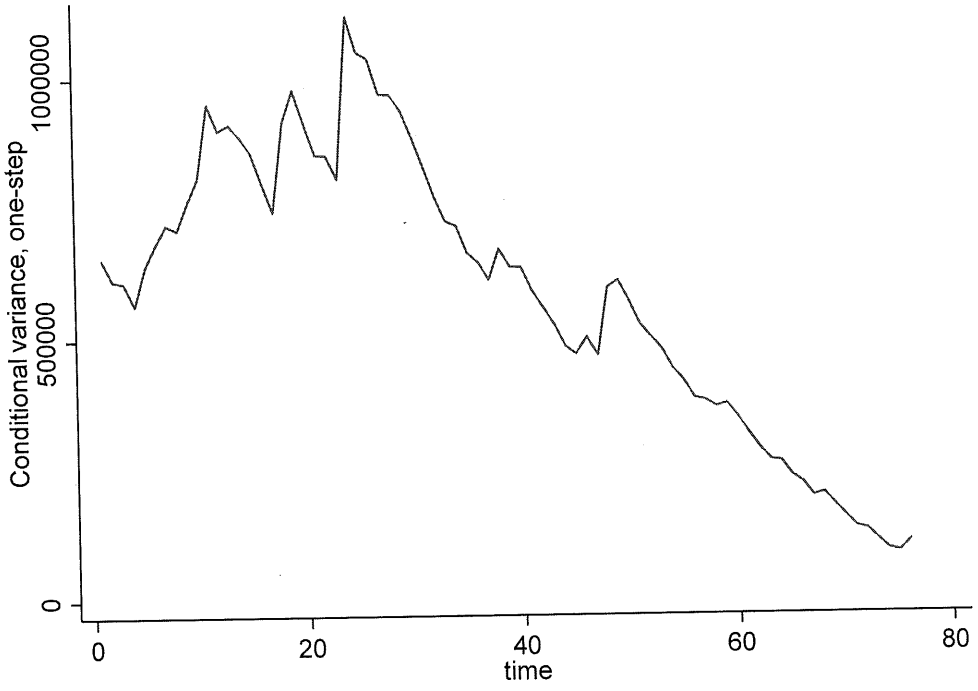

Chart 2. S&P 500 Volatility Index (US VIX)