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EMPIRICAL EVIDENCE ON BITCOIN RETURNS AND PORTFOLIO VALUE

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ABSTRACT

This paper studies 60 months of recent returns to examine relationships between bitcoin and 16 exchange-traded funds of currencies, bonds, stocks, commodities, and alternative assets. Bitcoin provides much higher returns, positive skewness, volatility and extreme returns, than all the other assets. Only stocks offer a better risk-return tradeoff than bitcoin. Bitcoin returns have very weak positive correlations with stocks, commodities, and alternatives. Only two funds of stocks and commodities have significant explanatory power of about 3% each for bitcoin returns. The full model of all the 16 funds explains only 15.09% of bitcoin returns. A partial model, with the six funds that are significant in the full model, explains 12.78% of bitcoin returns; 3 stock funds and 1 commodity fund have significant coefficients in this model. These findings indicate that bitcoin is a unique asset which is only weakly related to stocks and commodities. The results also show that small allocations to bitcoin improve the risk-return tradeoffs of stock and bond portfolios.

JEL: G11, G12

KEYWORDS: Cryptocurrencies, Bitcoin, Return Distributions, Explanatory Factors, Optimal Portfolios

INTRODUCTION

Cryptocurrencies emerged after a pseudonymous paper issued to a cryptography mailing list by Nakamoto (2008) detailed a peer-to-peer system of direct online payments with no financial intermediation. A cryptocurrency is an electronic currency using cryptography to verify transactions and create currency. The validated chain of transactions is recorded in a distributed public ledger (blockchain) based on a computer-intensive proof-of-work method. The first successful verifier of the longest blockchain, adding new transactions to the previous blockchain, is rewarded with new coins and may also charge a transaction fee. The difficulty of this mining process increases over time to offset advances in computing power so that the supply of coins increases at a stable rate.

In January 2009, Nakamoto mined 50 units of the first cryptocurrency (bitcoin) and released the related open source software; a computer programmer downloaded the software and received 10 bitcoins. The reward for successfully mining bitcoins is halved after every 210,000 blocks, in about four years, and the total supply is limited to 21 million, which is expected to be reached around 2040. Yermack (2015) indicated that the first bitcoin trade occurred on the Japanese online exchange Mt. Gox in 2010, when 20 bitcoins were traded at a price of 4.951 cents. Wallace (2011) reported that in the first retail transaction using bitcoin, a programmer had two pizzas delivered for 10,000 bitcoins paid to an intermediary.

The use and holdings of cryptocurrencies have increased substantially since they were created less than a decade ago. At the end of June 2018, there are 1,597 cryptocurrencies with total market capitalization of $255 billion (coinmarketcap.com). Bitcoin is the dominant cryptocurrency; there are 17.12 million bitcoins with market capitalization of $109 billion and average daily trading volume of $3.5 billion (www.blockchain.com/markets). By contrast, the second-largest cryptocurrency (ehtereum) has market capitalization of $45 billion and average daily trading volume of $1.2 billion. There are 3,391 bitcoin ATMs around the world, located mostly in North America (74.31%) and Europe (21.44%) (coinatmradar.com). However, only 36% of these ATMs buy and sell bitcoins; 64% of them only sell bitcoins. ATM transactions involve steep fees, averaging 9.27% for buying and 8.11% for selling bitcoins. Coinbase Commerce does not charge any merchant fee for accepting cryptocurrency payments in non-custodial accounts. Bitcoin payments are accepted by 48,000 merchants, including Bloomberg, Dish, Expedia, Intuit, Microsoft, Newegg.com, Paypal, Subway and Time (www.blockchain.com/clients, www.businessinsider.com). CBOE Global Markets launched trading in Bitcoin futures on December 10, 2017, enabling hedging of bitcoin exposure or benefitting from its performance, and listed the following benefits for traders: transparency, efficient price discovery, deep liquidity, and centralized clearing (cfe.cboe.com). The Chicago Mercantile Exchange also introduced bitcoin futures trading on December 17, 2017.

Government agencies have been compelled to respond to the proliferation and rapid adoption of cryptocurrencies. Appearing before the Senate Banking Committee on February 27, 2014, the Federal Reserve Chairwoman remarked that “my understanding is bitcoin doesn't touch U.S. banks" and "the Fed doesn't have authority to supervise or regulate bitcoin in any way." The Internal Revenue Service issued a notice (IR-2014-36) on March 2, 2014, observing that although virtual currency, such as bitcoin, operates like “real” currency in some environments, it is not legal tender in any jurisdiction. The notice stated that virtual currency is treated as property for federal tax purposes, implying that wages and payments to independent contractors and service providers paid in virtual currencies, as well as gains or losses on sales of virtual currencies, are subject to taxes. On August 11, 2014, the Consumer Financial Protection Bureau issued a consumer advisory warning against several potential risks of virtual currencies like bitcoin: ambiguous costs, volatile prices, hacking, scams, and inability to recover lost or stolen funds.

Some recent papers have discussed the features, benefits, limitations, and risks of this innovative new asset. Yermack (2015) argued that bitcoin does not fulfill the basic medium of exchange, store of value, and unit of account functions of a valid currency. He pointed out that the volume of bitcoin transactions is very low, bitcoin prices are far more volatile than the prices of widely used currencies, and the very high price of bitcoin requires consumer goods to be quoted in many decimals with leading zeroes. Harwick (2016) observed that cryptocurrencies possess several intrinsic characteristics of an exchange commodity that might be used as money. They are highly portable because they can be exchanged using any device carrying a wallet file; very durable since they are not a physical commodity which can depreciate; divisible up to eight decimal places; and secured by a protocol which requires forgers to possess more than half of the total computing power on the network. The author, however, noted that the shortcomings of cryptocurrencies as a medium of exchange are that they are not very widely accepted and liquid, and their values are extremely volatile. Baur et al. (2018) noted that, while a currency is a medium of exchange, unit of account, and store of value, an asset is only a store of value.

Indera et al. (2017) listed several desirable features of bitcoins: low transaction costs, limited supply, store of value function, and ease of international transfers. Coco et al. (2017) discussed the benefits of using bitcoin for consumers. The supply is limited and does not need to be regulated by a central authority to prevent inflation. The transactions offer more anonymity than traditional electronic payments. Online purchases and international transfers can be made at very low cost. The transactions can be for very small amounts and cannot be reversed. Böhme et al. (2015) highlighted several distinctive risks faced by bitcoin users: market, liquidity, counterparty, transaction, operational, privacy, legal, and regulatory risks. Harwick (2016) pointed out that governments cannot abolish cryptocurrencies because their protocols cannot be shut down, but governments can prevent stabilization of the purchasing power of cryptocurrencies by financial intermediaries, making them too volatile to replace centrally issued sovereign currencies.

Empirical issues of interest to investors and academics are the relationships between cryptocurrencies and other assets, and the potential of cryptocurrencies to improve the risk-return tradeoffs of portfolios of traditional assets. The few studies that have analyzed bitcoin returns used daily or weekly returns over limited periods when the returns were extremely high due to very low beginning prices. This is the first study to conduct a detailed investigation of bitcoin returns using monthly returns for a recent 60-month period. The study is limited to bitcoin because it is the cryptocurrency with the longest trading history and largest trading volume. The distribution of bitcoin returns is compared to 16 investable exchange-traded funds (ETFs) representing currencies, bonds, stocks, commodities, and alternative assets. The correlations between the returns of bitcoin and the ETFs are examined to determine whether any of these ETFs is similar to bitcoin. The extent to which bitcoin returns can be explained by the ETF returns is measured with univariate and multivariate regression models. The compositions of optimal portfolios maximizing the Sharpe ratio are identified to investigate whether bitcoin can enhance risk-return tradeoffs for investors.

LITERATURE REVIEW

Some researchers have tried to identify the motives of bitcoin users. Meiklejohn et al. (2013) reported that more than 60% of bitcoins mined during 2009-10 had not been spent, or were spent after more than a year, indicating that bitcoins are generally being held long-term. Glaser et al. (2014) found that new bitcoin users mostly limit themselves to trading on exchanges, suggesting that they view digital currencies as alternative investments rather than as payment mechanisms. Harwick (2016) noted that the demand for bitcoin is highly volatile and, according to some estimates, up to 90% of bitcoin transactions are speculative. Baur et al. (2018) observed that one-third of bitcoins are held by investors, indicating that it is mainly used as a speculative investment.

Several studies have investigated the fundamental drivers of cryptocurrency prices. Bouoiyour and Selmi (2015) performed bounds tests using an autoregressive distributed lag model with daily bitcoin prices and variables representing investors' attractiveness, trading volume, velocity of money, estimated output volume, hash rate, gold price, and the Shanghai market index. They concluded that bitcoin is a speculative asset and it might be used for economic reasons, but it is not a safe-haven asset. Kristoufek (2015) conducted wavelet coherence analysis and found that, although bitcoin is generally considered to be a speculative asset, its prices are influenced by fundamental factors, such as trade use, money supply, and price level. This study also reported that bitcoin prices are driven by investors' interest, indicated by Google and Wikipedia searches. Ciaian et al. (2016) showed that bitcoin prices are significantly related to market forces of supply and demand, especially demand factors such as size of the bitcoin economy, particularly after September 2013 when bitcoin was more established. In the long run, bitcoin prices are also influenced by attractiveness for investors and users, but not by macro-financial variables. A study of 66 of the most widely used cryptocurrencies by Hayes (2017) revealed that 84% of relative values can be explained by the competition level in the producers' network, production rate, and difficulty of the mining algorithm. Wang and Vergne (2017) showed that weekly bitcoin returns are significantly positively related to the innovation potential of technological upgrades, negatively related to public interest, and not significantly influenced by media reports of fraudulent activity.

Bitcoin has been compared to gold and currencies. Dyhrberg (2016a) noted several similarities between bitcoin and gold: the supplies are limited and not controlled by a government, the values are mainly derived from scarce supply, and the prices are highly volatile. The author found that daily bitcoin returns are not significantly related to returns on the Financial Times Stock Exchange 100 index, indicating that bitcoin has diversification potential like gold. Based on a GARCH volatility analysis, Dyhrberg (2016b) concluded that bitcoin exhibits characteristics of both gold, which is a store of value, and the U.S. dollar, which is a medium of exchange, suggesting that it can be useful for portfolio management. Dwyer (2015), however, reported that bitcoin has a much higher average monthly volatility of returns than gold and foreign currencies against the dollar.

Owing to the very short trading history of bitcoin, there is limited evidence of the relationships between the returns of bitcoin and other assets. Brière et al. (2015) studied weekly returns from July 2010 to December 2013 and found that bitcoin spans traditional assets (currencies, stocks, and bonds) as well as alternative assets (commodities, real estate, and hedge funds). They also reported that even small allocations to bitcoin provide significant diversification benefits and substantially enhance the risk-return tradeoffs of well-diversified portfolios. Analysis of daily and weekly returns from July 2011 to December 2015 by Bouri et al. (2017) showed that bitcoin is an effective diversifier for U.S. stocks and bonds, international equities, U.S. dollars, and commodities, including oil and gold, but it is a poor hedge, providing a strong safe haven only for weekly returns in Asian stocks. Baur et al. (2018) reported that, between July 2010 and June 2015, bitcoin provided higher daily returns than 16 other assets, but it also had the highest volatility and very high negative skewness and kurtosis.

Review of the existing literature reveals several interesting findings that highlight the value of this study. Since bitcoin is mostly regarded as an investment or a speculative asset, it is important to determine the nature of this asset and its value as a portfolio component. Encouragingly, bitcoin prices are related to several endogenous and exogenous fundamental factors, implying that they cannot be completely irrational. The evidence also suggests that bitcoin offers diversification benefits and may be useful for portfolio management, which is investigated in this study.

DATA AND METHODOLOGY

Daily prices of bitcoin (BTC) were downloaded from coinmarketcap.com/currencies/bitcoin/historical-data/, which calculates the volume-weighted average of prices reported in all the markets where BTC is traded. Since BTC can be traded round the clock, there are no closing prices. Consistent with common practice, Coinmarketcap reports daily prices at Coordinated Universal Time, which corresponds to 8 p.m. Eastern Standard Time (EST) in the United States. This creates a four-hour time difference between the daily BTC prices and closing prices of U.S. financial assets which are reported at 4 p.m. EST. The nonsynchronous prices of BTC and other financial assets pose a greater problem for studies using daily or weekly returns than for those based on monthly returns, because the effect of any material news on bitcoin prices during the four-hour time lag between the closing prices of bitcoin and other financial assets on the beginning and ending days will be smaller over longer horizons. Since Coinmarketcap provides daily BTC prices starting on April 28, 2013, this study is based on 60 monthly returns, from May 2013 through April 2018. Closing prices, adjusted for dividends and stock splits, of 16 large ETFs drawn from five major asset classes, were downloaded from finance.yahoo.com/quote/, which reports the data from Intercontinental Exchange, owner of the New York Stock Exchange. The ETFs are listed in Table 1.

Table 1: List of Exchange-Traded Funds Used to Explain Bitcoin Returns

Symbol	Description
Currencies	
CEW	WisdomTree Emerging Currency Strategy: emerging market currencies
UUP	Invesco D.B. U.S. Dollar Bullish: Deutsche Bank long U.S. dollar currency portfolio
Bonds	
BOND	PIMCO Active Bond: diversified portfolio of fixed-income instruments
IBND	SPDR Barclays Bloomberg International Bond: global corporate bond index ex-U.S.D.>$1B
HYG	iShares iBoxx $ High Yield Corporate Bond: liquid high-yield index
ZROZ	PIMCO 25+Year Zero Coupon U.S. Treasury: U.S. Treasury principal STRIPS index
Stocks	
ACWI	iSHARES MSCI: large- and mid-capitalization emerging market equities
QQQ	Invesco QQQ Trust: NASDAQ-100 Index
SCHF	Schwab International Equity: FTSE developed ex-U.S. index
SPY	SPDR S&P 500: S&P 500 Index
Commodities	
DBC	Invesco D.B. Commodity Tracking: D.B.I.Q. optimum yield diversified commodity index
GLD	SPDR Gold Shares: gold bullion
USCI	U.S. Commodity Index: SummerHaven dynamic commodity index total return
USO	U.S. Oil: benchmark short-term oil futures contract
Alternatives	
PSP	Invesco Global Listed Private Equity: Red Rocks global listed private equity index
QAI	I.Q. Hedge Multi-Strategy Tracker: I.Q. hedge multi-strategy index fund of funds

Ticker symbols and brief descriptions of 16 exchange-traded funds used to explain Bitcoin returns.

Monthly returns of BTC and the 16 ETFs were calculated using prices on the last trading day of each month for the ETFs. For example, the returns for April 2018 were based on the differences between the prices on March 29 and April 30, 2018, although BTC continued trading during the weekend (March 30 and 31), when the ETFs were not trading. This procedure ensured consistent return intervals for computing BTC and ETF returns. The continuously compounded monthly return (RET) of each asset was computed as:

$$\text{RET} = \text{Natural Log (Month Closing Price / Previous Month Closing Price)} \quad (1)$$

The investigation of BTC returns involved comparing the distribution of its returns with ETF returns, examining correlations between the returns of BTC and ETFs, conducting univariate and multivariate regressions of BTC returns against the ETF returns, and determining the optimal allocations of portfolios containing SPY, BOND, and BTC, which maximize the Sharpe ratio (SR). To compare the distributions, the mean, median, standard deviation (SD), skewness, and kurtosis of RET for each asset over the 60-month study period were obtained with Excel's average, median, stdev, skew, and kurt functions, respectively. The risk-return tradeoffs provided by the assets were measured with the coefficient of variation (CV):

$$\text{CV} = \text{Standard Deviation of Returns/ Mean Return} \quad (2)$$

The risk-premium per unit of total risk was determined with the SR, using the iShares Short Treasury Bond ETF (SHV), which comprises U.S. treasury bonds maturing within a year, as the risk-free security:

$$\text{SR} = (\text{Mean Asset Return} - \text{Mean Riskfree Return}) / \text{Standard Deviation of Asset Return} \quad (3)$$

Normality of the return distributions was tested with the Jarque-Bera (JB) test statistic, which is based on a joint test of the null hypothesis that the skewness and kurtosis are not significantly different from the normal distribution:

$$\text{JB Statistic} = \frac{N}{6}(\text{Skewness}^2 + \text{Kurtosis}^2/\ 4) \quad (4)$$

Univariate regressions of BTC returns against returns of each of the 16 ETFs are based on the following model:

$$\text{BTC RET} = \alpha + \beta \text{ ETF RET} \quad (5)$$

The model for multivariate regressions of BTC returns against returns of the full and partial models of the 16 ETFs is:

$$\text{BTC RET} = \alpha + \beta_1 \text{ ETF RET}_1 + \cdots + \beta_N \text{ ETF RET}_N \quad (6)$$

EMPIRICAL RESULTS

Table 2 displays the distributional properties and risk-return tradeoffs of monthly returns of BTC and the ETFs representing different financial asset classes. The mean return of 6.99% on BTC is almost five times the second-highest mean return of 1.46% for QQQ, and BTC's SD of 31.25% is more than three times the second-highest SD of 8.61% for USO. The huge return offered by BTC compensates for its very high risk, resulting in a CV of 4.47, which is lower than the CVs of 5.65 to 80.21 for the bonds and in line with the CVs of 2.49 to 6.79 for the stocks. While most of the ETF returns are negatively skewed, BTC is the only asset that has a high positive skew of 2.42, its mean return exceeding the median return by 1.01%. This finding based on monthly returns contrasts with the result of Baur et al. (2018) that daily bitcoin returns are highly negatively skewed. BTC also has a very high kurtosis of 12.06, which is more than seven times the second-highest kurtosis of 1.60 for BOND. BTC has a very large JB statistic, which is significant well below the 1% level, and BOND is the only other asset whose JB statistic is significant, at 5% level, indicating that their returns are not normally distributed. BTC has the fourth-highest SR of 0.22; the three highest SRs of 0.40, 0.35, and 0.24, are all provided by stocks (QQQ, SPY, and ACWI). Overall, these data show that BTC is a unique asset. It provides very high returns that are highly positively skewed but come with high risk in terms of volatility as well as extreme returns. However, it offers a mean-variance tradeoff which is second only to that of stocks.

Table 2: Statistics of Monthly Returns on Bitcoin and Exchange-Traded Funds

Asset	Mean	Median	SD	CV	Skew	Kurtosis	JB Statistic	Sharpe Ratio
BTC	6.99%	5.98%	31.25%	4.47	2.42	12.06	421.91***	0.22
Currencies								
CEW	-0.15%	-0.05%	2.11%	-14.06	0.10	0.12	0.14	-0.08
UUP	0.14%	0.22%	1.95%	13.89	0.03	-0.47	0.57	0.07
Bonds								
BOND	0.16%	0.16%	0.98%	6.34	-0.10	1.60	6.48**	0.15
IBND	0.03%	-0.06%	2.17%	80.21	-0.06	0.49	0.64	0.01
HYG	0.27%	0.40%	1.50%	5.65	-0.20	-0.45	0.91	0.17
ZROZ	0.24%	0.24%	5.08%	21.43	0.02	0.82	1.68	0.05
Stocks								
ACWI	0.72%	1.10%	2.95%	4.10	-0.18	0.29	0.54	0.24
QQQ	1.46%	1.93%	3.64%	2.49	-0.04	-0.08	0.03	0.40
SCHF	0.48%	0.70%	3.24%	6.79	-0.10	-0.30	0.32	0.14
SPY	1.01%	1.10%	2.83%	2.81	-0.15	0.26	0.40	0.35
Commodities								
DBC	-0.67	-0.21	4.31%	-6.42	-0.52	0.51	3.37	-0.16
GLD	-0.23%	-0.39%	4.52%	-19.92	0.04	-0.06	0.02	-0.05
USCI	-0.39%	-0.13%	2.87%	-7.37	-0.49	0.61	3.37	-0.14
USO	-1.46%	-1.23%	8.61%	-5.89	-0.49	0.56	3.16	-0.17
Alternatives								
PSP	0.73%	1.23%	3.83%	5.22	-0.16	-0.27	0.42	0.19
QAI	0.16%	0.22%	1.19%	7.32	0.13	0.13	0.21	0.13

*Descriptive statistics and Sharpe ratios of monthly returns of Bitcoin and 16 exchange-traded funds used to explain Bitcoin returns. The JB statistic jointly tests the null hypotheses that the skew and kurtosis are not significantly different from normal. JB statistics significant at the 1%, 5% and 10% levels are denoted by ***, ** and *, respectively.*

Table 3 shows that BTC returns have little to no correlation with returns of the other assets. The highest correlations of its returns are with stocks (QQQ and SPY), commodities (USCI), and alternatives (QAI), but these correlations are weak (0.20 to 0.22). The weak correlations between the returns of BTC and other assets reinforce the findings based on the comparison of their distributions. BTC is unlike any other asset, although it displays weak similarities to stocks, commodities, and alternatives. Stock returns are highly correlated with each other as well as with alternatives. The only strong correlation among bonds is between BOND and ZROZ. HYG returns are strongly correlated with stocks and alternatives. Commodity returns are strongly correlated with each other, except for GLD. UUP returns have moderate negative correlations with most of the other assets; its strongest negative correlations are with IBND (-0.91) and CEW (-0.68). Strong correlations between several assets indicate that multivariate models will be affected by multicollinearity.

Table 4 presents the results of univariate regressions of BTC returns against returns of the other assets. Half of the regression models have intercepts that are significant (at 10% level) and only two ETFs have coefficients that are significant, both at 10% level. The R-squares are very low, ranging from 0.01% to 4.76%. Based on the adjusted R-squares, returns of QQQ and UCSI explain 3.11% and 2.99%, respectively, of BTC returns. The only other ETFs whose returns explain more than 1% of BTC returns are SPY (2.55%) and QAI (2.20%), but their coefficients are not significant.

Table 3: Correlations of Returns on Bitcoin and Exchange-Traded Funds

	Currencies			**Bonds**				**Stocks**			
	BTC	**CEW**	**UUP**	**BOND**	**HYG**	**IBND**	**ZROZ**	**ACWI**	**QQQ**	**SCHF**	**SPY**
Currencies											
CEW	0.05										
UUP	-0.01	-0.68									
Bonds											
BOND	0.06	0.39	-0.04								
HYG	0.14	0.58	-0.33	0.44							
IBND	0.12	0.68	-0.91	0.22	0.43						
ZROZ	-0.07	0.09	0.11	0.79	0.13	0.06					
Stocks											
ACWI	0.16	0.63	-0.42	0.22	0.71	0.52	-0.14				
QQQ	0.22	0.36	-0.21	0.12	0.50	0.36	-0.17	0.85			
SCHF	0.12	0.66	-0.48	0.29	0.71	0.56	-0.11	0.95	0.77		
SPY	0.20	0.44	-0.25	0.06	0.63	0.38	-0.21	0.94	0.88	0.80	
Commodities											
DBC	0.12	0.47	-0.47	-0.13	0.51	0.39	-0.34	0.37	0.11	0.39	0.25
GLD	-0.03	0.37	-0.33	0.48	0.37	0.34	0.48	0.03	-0.07	0.08	-0.09
USCI	0.22	0.48	-0.53	-0.06	0.37	0.45	-0.23	0.35	0.15	0.36	0.23
USO	-0.01	0.36	-0.39	-0.24	0.40	0.31	-0.43	0.32	0.13	0.36	0.23
Alternatives											
PSP	0.07	0.47	-0.41	0.12	0.66	0.47	-0.24	0.90	0.77	0.90	0.82
QAI	0.20	0.58	-0.43	0.34	0.70	0.57	0.00	0.85	0.73	0.80	0.80
	Commodities				**Alternatives**						
	DBC	**GLD**	**USCI**	**USO**	**PSP**						
Commodities											
GLD	0.27										
USCI	0.82	0.35									
USO	0.88	0.05	0.65								
Alternatives											
PSP	0.32	-0.02	0.24	0.32							
QAI	0.37	0.21	0.39	0.25	0.74						

Correlations of monthly returns of Bitcoin and 16 exchange-traded funds used to explain Bitcoin returns.

The full-model regression in Table 5 shows that returns of the 16 ETFs have a combined R-square of 38.12%, but the large number of independent variables results in considerable shrinkage of explanatory power, reducing the adjusted R-square to only 15.09%. The F-statistic is significant at 10% level. Six variables have significant coefficients: USO, ACWI, and SPY at 5% level; and USCI, SCHF, and BOND at 10% level. Consistent with the univariate regression coefficients, BTC is positively related to SPY, USCI, SCHF and BOND, and negatively related to USO. The only ETF which is significant in the full model and has a coefficient that changes sign, from positive in the univariate regression to negative in the multivariate regression, is ACWI. This may be attributed to multicollinearity; Table 3 showed that ACWI is strongly correlated with the stocks, alternatives, and HYG.

Table 4: Univariate Regressions of Monthly Returns on Bitcoin against Exchange-Traded Funds

	Intercept	T-Statistic	Coefficient	T-Statistic	R-Square	Adj. R-Square
Currencies						
CEW	0.07*	1.74	0.67	0.34	0.20%	-1.52%
UUP	0.07*	1.72	-0.19	-0.09	0.01%	-1.71%
Bonds						
BOND	0.07	1.63	1.95	0.47	0.38%	-1.34%
IBND	0.07*	1.72	1.78	0.95	1.53%	-0.17%
HYG	0.06	1.51	3.01	1.11	2.10%	0.41%
ZROZ	0.07*	1.75	-0.44	-0.54	0.51%	-1.21%
Stocks						
ACWI	0.06	1.40	1.65	1.20	2.42%	0.74%
QQQ	0.04	0.99	1.87*	1.70	4.76%	3.11%
SCHF	0.06	1.58	1.15	0.92	1.42%	-0.27%
SPY	0.05	1.11	2.26	1.59	4.20%	2.55%
Commodities						
DBC	0.08*	1.85	0.84	0.89	1.34%	-0.37%
GLD	0.07*	1.70	-0.24	-0.26	0.12%	-1.60%
USCI	0.08*	1.97	2.35*	1.68	4.64%	2.99%
USO	0.07*	1.68	-0.04	-0.08	0.01%	-1.71%
Alternatives						
PSP	0.07	1.59	0.60	0.56	0.54%	-1.17%
QAI	0.06	1.53	5.17	1.53	3.86%	2.20%

*Univariate regressions of monthly Bitcoin returns against returns of 16 exchange-traded funds, based on the model: BTC RET = a + ß ETF RET. Intercepts and coefficients significant at the 1%, 5% and 10% levels are denoted by ***, ** and *, respectively.*

Table 5: Multivariate Regressions of Monthly Returns on Bitcoin Against Exchange-Traded Funds

	Full Model		Partial Model	
	Coefficient	T-Statistic	Coefficient	T-Statistic
Intercept	0.00	0.10	0.03	0.63
Currencies				
CEW	1.47	0.36		
UUP	7.14	1.06		
Bonds				
BOND	17.25*	1.73	6.38	1.29
IBND	8.56	1.51		
HYG	0.50	0.09		
ZROZ	-1.99	-1.11		
Stocks				
ACWI	-41.44**	-2.17	-34.77**	-2.35
QQQ	3.10	1.16		
SPY	23.75**	2.19	22.56***	2.75
SCHF	15.38*	1.75	13.89*	1.88
Commodities				
DBC	5.57	1.64		
GLD	-2.06	-1.49		
USCI	4.85*	1.77	6.15***	3.11
USO	-2.87**	-2.48	-0.96	-1.49
Alternatives				
PSP	-1.07	-0.36		
QAI	-6.17	-0.84		
F-Statistic	1.66*		2.44**	
R-Square	38.12%		21.65%	
Adj. R-Square	15.09%		12.78%	

Multivariate regressions of monthly Bitcoin returns against returns of exchange-traded funds, based on the model: BTC RET = a + β_1 *ETF* RET_1 *+ … +* β_N *ETF* RET_N*. Intercepts and coefficients significant at the 1%, 5% and 10% levels are denoted by ***, ** and *, respectively.*

A partial-model regression, using only the six variables with significant coefficients in the full-model regression, produces an F-statistic that is significant at 5% level, although the explanatory power of 12.78%, indicated by the adjusted R-square, is a bit lower compared to the full model. In this partial model, the coefficients are significant at 1% level for USCI and SPY, 5% level for ACWI, and 10% level for SCHF, while BOND and USO do not have significant coefficients. Overall, these findings show that the other asset returns do not have much explanatory power for BTC returns. The only assets whose returns have some explanatory power for BTC returns are stocks and commodities, which are generally positively related to BTC returns.

Table 6 determines whether investing in BTC can improve the risk-return tradeoff for stock and bond investors, by examining the characteristics of optimal portfolios maximizing the SR. Portfolio 1, comprising the traditional assets, allocates 51.63% to BOND and 48.37% to SPY, providing a SR of 0.38, which is higher than the SRs of 0.15 for BOND and 0.35 for SPY in Table 2. Compared to investing in BOND alone, allocating 95.25% to BOND and 4.75% to BTC increases the SR by 73% to 0.26 because the mean return triples while the SD increases by 84%. Relative to investing only in SPY, an optimal portfolio comprising 95.73% SPY and 4.27% BTC increases the SR by 10% to 0.39, as the mean return rises by 25% and the SD increases by 15%. Portfolio 4, which considers investing in all the three assets, is identical to portfolio 3 because BOND receives a 0.00% weight, indicating that adding it does not improve the risk-return tradeoff of a portfolio comprising SPY and BTC. These results suggest that small allocations to BTC can improve the risk-return tradeoffs of stock and bond portfolios.

Table 6: Optimal Portfolios of Stocks, Bonds, and Bitcoin

	Portfolio 1	**Portfolio 2**	**Portfolio 3**	**Portfolio 4**
	SPY & BOND	**BOND & BTC**	**SPY & BTC**	**SPY, BOND & BTC**
Allocations				
SPY	48.37%		95.73%	95.73%
BOND	51.63%	95.25%		0.00%
BTC		4.75%	4.27%	4.27%
Characteristics				
Mean Return	0.57%	0.48%	1.26%	1.26%
Median Return	0.69%	0.46%	1.48%	1.48%
Standard Deviation	1.49%	1.80%	3.26%	3.26%
Coefficient of Variation	2.62	3.76	2.58	2.58
Skew	-0.10	0.85	0.04	0.04
Kurtosis	0.22	3.50	0.65	0.65
JB Statistic	0.22	37.86***	1.09	1.09
Sharpe Ratio	0.38	0.26	0.39	0.39

*Portfolio allocations, descriptive statistics and Sharpe ratios of optimal portfolios maximizing the Sharpe ratio for portfolios of stocks, bonds, and Bitcoin. The JB statistic jointly tests the null hypotheses that the skew and kurtosis are not significantly different from normal. JB statistics significant at the 1%, 5% and 10% levels are denoted by ***, ** and *, respectively.*

It may be noted that the optimal portfolios have very different characteristics. Portfolio 2 (BOND & BTC) has the lowest mean return and second-highest SD, resulting in the highest CV and lowest SR. It is also the only optimal portfolio that is highly positively skewed and has high kurtosis, with the highly significant JB statistic indicating that the returns are not normally distributed. Portfolios 1 and 3 deliver similar SRs with risk-return profiles that are strikingly different. The mean return and SD of portfolio 3 are more than twice those of portfolio 1. The choice between these two portfolios involves deciding whether to optimize the risk-return tradeoff of a stock portfolio with a large allocation to bonds or a small allocation to bitcoin, a decision that depends on investors' appetite for risk and hunger for returns.

CONCLUSIONS

This study investigates whether bitcoin is similar to 16 investable ETFs of currencies, bonds, stocks, commodities, and alternative assets, using 60 months of recent returns. The results show that bitcoin provides much higher and far more positively skewed returns, with much greater volatility and extreme returns, compared to all the other assets. Yet, bitcoin offers a mean-variance tradeoff that is second only to that of stocks; only three stock funds provide higher Sharpe ratios than bitcoin. Bitcoin returns are generally not correlated with the ETF returns; there are very weak positive correlations with stocks, commodities, and alternatives. Only two ETFs, representing stocks and commodities, have significant but weak explanatory power, of about 3% each, for bitcoin returns. The full model with all the 16 ETFs generates combined explanatory power of 15.09% for bitcoin returns. A partial model, with the six ETFs that have significant coefficients in the full model, provides explanatory power of 12.78%, and four ETFs (3 stock funds and 1 commodity fund) retain significant coefficients in this model. These results indicate that bitcoin returns have a unique distribution, and only stocks and commodities have weak positive correlations and explanatory power for bitcoin returns. Consistent with these results, indicating the diversification potential of bitcoin, adding small proportions of bitcoin enhances the Sharpe ratio of stock and bond portfolios.

Since cryptocurrencies are a fairly recent innovation and bitcoin is the only cryptocurrency with historical monthly returns data available for a reasonably long period, this study is based on the limited data available for one cryptocurrency and it investigates relationships between bitcoin and several exchange-traded funds representing five financial asset classes. As bitcoin and other cryptocurrencies establish longer trading histories, this study can be extended by investigating relationships between a broader group of cryptocurrencies and major asset classes for longer periods.

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