Title
Changes In Crypto Markets And Traditional Markets: How They Interact & Cryptocurrency’s Viability As An Investment Opportunity

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CHANGES IN CRYPTO MARKETS AND TRADITIONAL MARKETS: HOW THEY INTERACT & CRYPTOCURRENCY'S VIABILITY AS AN INVESTMENT OPPORTUNITY

By

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A capstone submitted for Graduation with University Honors

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ABSTRACT

While previous studies have concluded that cryptocurrencies are relatively unresponsive to changes in the macroeconomic environment and exhibit risk-return tradeoffs that are distinct from those on traditional asset classes, such as stocks, currencies, and commodities, recent findings from the CFA institute and reports by traditional media outlets have indicated that returns on cryptocurrencies are becoming increasingly correlated with returns on traditional assets. Given the relative novelty of cryptocurrencies, it is reasonable to assume that their behavior, as well as our understanding of it is dynamic. Taking this developing trend into consideration, this paper reevaluates their relationship and cryptocurrency's viability as an investment opportunity by comparing Bitcoin and Ethereum returns with returns on commodities and proxies for multiple market economies. Through regression and correlation tests, I find that, while other factors influence Bitcoin and Ethereum returns, returns on western and global market proxies demonstrate some explanatory power for the returns on the coins selected. Furthermore, I find that cryptocurrencies exhibit higher than average risk-adjusted returns, potentially making them an appealing option to risk-seeking investors.

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1. Background

1.1 Overview & Uses

Introduced in 2009, Bitcoin is considered to be the first cryptocurrency created. Since then, a host of altcoins, or cryptocurrencies other than bitcoin, have emerged to capitalize on Bitcoin's growing popularity. Bitcoin and most other altcoins are decentralized forms of currency. Whereas traditional, fiat currencies, such as the U.S. dollar or the Euro, derive their value from the full faith and credit of the central bank or entity issuing them, decentralized currencies do not. Bitcoin's intended purpose was to serve as an inexpensive means of electronic, peer-to-peer payment that circumvents the need for intermediation from financial institutions or governments (Castro, 2020). As a payment method, Bitcoin has several potential advantages over traditional payment methods, such as lower costs, global reach, payer anonymity, and superior speed of settlement. It is also heavily dependent on information technology and networks, highly volatile, and its lack of transparency, due to user anonymity, can lead to an increased risk of fraud (Saksonova, 2019). However, applications for cryptocurrencies have expanded beyond merely transferring money, and they are now being considered for their ability to serve as investment opportunities and stores of value (Farell, 2015). As a result, questions surrounding how these assets should be valued have arisen.

1.2 Mining & The Blockchain

Instead of being issued by a central authority, cryptocurrencies are generated through a process known as mining and are stored as blocks on the blockchain, which, in the case of larger cryptocurrencies such as Bitcoin and Ethereum, are public ledgers that can be used to verify a coin's owner while simultaneously keeping their true identity confidential through the use of pseudonyms. In simple terms, the mining process consists of utilizing extreme amounts of computational power to solve complex math problems. Once a problem is solved, the transaction is verified and added to the digital ledger as a block on the chain, indicating the solver's ownership of the block. In cryptocurrencies that operate on a distributed ledger, each user on a decentralized blockchain network has an identical copy of the data stored on the ledger - allowing anyone on the network to identify who maintains ownership over a given block based on the pseudonym assigned to it (Hughes, 2017). Thus, the distributed ledger serves as an immutable, unchanging, and somewhat transparent method for keeping track of cryptocurrency ownership.

1.3 Valuation

Unlike stocks, which have underlying companies from which they derive their value, and commodities, which have inherent value to buyers, cryptocurrencies are non-physical assets with no underlying entity to identify as the basis for their value. Since traditional valuation methods, such as discounted cash flow analyses, are not readily applicable to cryptocurrencies, ways to evaluate their actual worth are limited. As a result, several theories have emerged regarding how to perform a valuation on this new class of asset. Cheung et al. (2013) asserts that since Bitcoin is anchored on a computer program and has no intrinsic value then it must derive its value purely from being a speculative commodity. Hayes (2017) generally maintains the assertion that cryptocurrencies have no intrinsic value. However, he postulates that valuation for bitcoin should occur based on the costs of production, or computational power, allocated to finding coins, the rate at which they can be mined, how long they have existed, and the percentage of coins left to be mined in the finite supply. These variables are constantly changing, and, therefore, the value of cryptocurrencies changes alongside them. While Hayes' model provides a framework with clear criteria for assigning value to cryptocurrencies beyond mere speculation, the underlying issues of high volatility and a lack of a central institution or physical assets backing them persist. Adopting a less mathematical approach, Carpenter (2016) hypothesized that a cryptocurrency's value is a function of its ability to serve as a currency and payment method and the distributed consensus network on which it operates. He further states that uncertainty about a coin's true function can lead to speculative bubbles, followed by abrupt price corrections. However, Bitcoin's ability to act as a currency is questionable, which will be discussed further in the following Behavior & Characteristics section.

1.4 Behavior & Characteristics

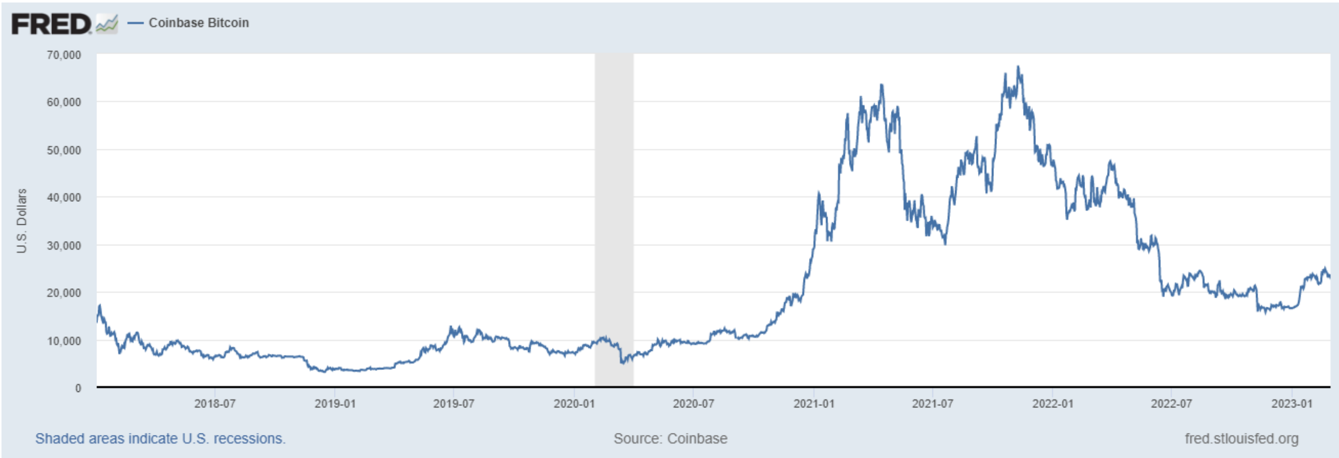
Although initially considered for their potential to replace fiat currencies, Cheung et al.'s (2015) study of cryptocurrency bubbles, proposed that cryptocurrencies, due to their high volatility, or extreme variability in price, cannot perform the same function as traditional currencies because they are incapable of acting as a store of value or unit of account. Instead, they reason that cryptocurrencies derive their value from being a speculative commodity, or a basic good used in commerce that is purchased with the expectation that its value will increase in the near future. Furthermore, Vidal-Tomás et al. (2019) found that cryptocurrency markets exhibited weak form market efficiency. Thus, prices for cryptocurrencies may not accurately reflect available information, making them prone to bubbles and creating opportunities for arbitrage. As previously mentioned, Liu & Tsyvinski's 2018 study found that cryptocurrencies have risk-return factors that are distinct from those on the traditional market, having no exposure to most common stock market and macroeconomic factors. Additionally, they determined that momentum and investor attention were key indicators that could be used to predict returns. Their findings were consistent with statements made by Carpenter (2016) and Lee et al. (2017) that Bitcoin maintains a low correlation to traditional assets. However, if media reports are correct in their assessment that cryptocurrencies have become more sensitive to the risk-return factors associated with traditional markets, then it is crucial to reassess these studies and determine their current relationship to better determine their viability as investment opportunities.

1.5 Viability as an investment

Understanding the behavior and characteristics of cryptocurrencies are key to helping inform theoretical interpretations of their potential to serve as investment vehicles. Moreover, empirical studies on their performance within portfolios and an understanding of the external environment surrounding them are equally crucial. While many studies have found that adding cryptocurrencies to a portfolio can improve returns when compared to those that are composed entirely of traditional assets, they each had caveats surrounding their findings. Petukhina et al. (2021) found that, due to higher average returns and low correlations to the market, cryptocurrencies can serve as alternative investment opportunities for portfolio and risk management. However, their study also found that investment in cryptocurrencies is not a catch-all for investors seeking superior portfolio performance. Like traditional assets, the benefits of including cryptocurrencies are highly dependent on several key factors: the investor's risk profile, benefiting those with higher risk tolerance; the liquidity of the cryptocurrency being traded; and the amount of diversity across cryptocurrencies. When assessing the potential benefit to investors, the results of Saksonova et al.'s (2019) study generally agree with the aforementioned considerations but adds that cryptocurrency investments should not be correlated, and regular rebalancing of the portfolio should be considered. Carpenter's (2016) study corroborates the assertion that cryptocurrencies can serve as useful diversification tools.

However, Carpenter found that a speculative bubble within their data set may have been responsible for the over performance of their observed portfolio containing Bitcoin. When controlling for the specific period from the sample, portfolios containing bitcoin underperformed their non-crypto counterparts. Similarly, Lee et al. (2017) found that investment in the cryptocurrency index, CRIX, expanded the efficient frontier of a portfolio initially composed of traditional assets, but that sentiment-induced mispricing was likely to occur - leading to corrections occurring during the trading day. When creating portfolios by mixing cryptocurrencies with assets tracking market indexes Castro et al. (2020) found that portfolios that invested in cryptocurrencies had greater returns, though, predictably, with higher risks accompanying those returns. As a result, they determined portfolios should still favor market assets over cryptocurrency assets. However, regulatory decisions are equally as important as portfolio performance when considering cryptocurrency's viability as an investment. Hughes (2017) states that cryptocurrencies are inherently difficult to regulate due to a combination of their decentralized nature causing them to not be confined to one legal jurisdiction, as well as a lack of a specific regulating entity. Consequently, customer protection is relatively absent. Additionally, Edwards et al. (2019) mention that fraudulent initial coin offerings; price manipulations, via pump-and-dump schemes; and cyberattacks on cryptocurrency exchanges are all issues that have yet to receive comprehensive regulation. As such, these are additional risks that investors must account for when considering cryptocurrencies as an investment opportunity. Overall, the general consensus is that cryptocurrencies have the capability of generating excess returns over what traditional assets offer by themselves. However, investor risk profile, liquidity, diversity, low correlation, and lack of regulation are all paramount considerations when determining their viability as investments.

2. Data



Price of 1 Bitcoin denominated in USD from Jan 2017-Feb 2023

I start by downloading historical data for asset prices and foreign exchange rates from Yahoo Finance, S&P Global, and Global Energy Price Index, which I will refer to as GEPI, data from the Federal Reserve Bank of St. Louis' website (FRED). Next, I gather monthly risk-free rates and momentum data from the Center for Research in Securities Prices on the Wharton Data Services (WRDS) website, over a five-year period from December 2017 to February 2023, I analyze the return performance and relationship between Bitcoin, Ethereum, and a multitude of market and commodity indexes and ETFs. The market indexes and ETFs used were the SPDR S&P 500 ETF (SPY), S&P Europe 350 (SPE350), MOEX Russia Index (IMOEX.ME), Hang Seng Index (HSI), S&P GSCI (SPGSCI), iShares MSCI World ETF (URTH), and S&P 1200 Global (SPG1200). Respectively, these indexes and ETFs were used as proxies for U.S., European, Russian, Chinese, commodities, and global markets, with URTH and SPG1200 being used as two different measures tracking the global economy. In using the return data for various market indexes, I aim to examine whether macroeconomic events of any given country, which should be reflected in returns on its corresponding market index, appear to have a tighter relationship with the cryptocurrencies observed than returns on other countries' indexes.

Although equities constitute the bulk of the assets being studied, I also elected to include S&P's GSCI ETF as a proxy for commodity markets to see how the relationship I observe compares to the findings presented in Liu & Tsyvinski's's 2018 study. Since Hayes (2017) proposed electricity prices as a major driver of cryptocurrency value formation, the GSCI was selected due to its heavy weighting in energy, with energy sector weightings constituting roughly 61.71%, 53.93%, 53.48%, and 61.47% of the overall index's value for 2020, 2021, 2022, and 2023, respectively. Despite using price data for the index from 2018-2023, I was unable to find data referencing index weights prior to 2020 so this paper assumes that the index's weightings remain consistently overweight in energy commodities. Ultimately, the objective in picking this index is to examine how returns on the broader commodity market compare to cryptocurrency returns. Furthermore, I compare Bitcoin, Ethereum, and GSCI returns to observe how they behave relative to shifts in global energy prices indicated by index data from FRED, in order to assess the overall impact of the energy component of the GSCI.

While a perfect proxy for any given market does not exist, this paper assumes that the indexes and ETFs selected are reasonable proxies for modeling general market performance. Consequently, I acknowledge that there are potentially other indexes and asset types that may model market performance better than those that I selected.

3. Methodology

3.1 CAPM & Jensen's α

Aggregating price data from the aforementioned sources into Excel, I used currency exchange rates that corresponded to price data for each given month to denominate the prices of each asset in United States Dollars (USD). With all assets denominated in common units, I calculated their monthly returns from January 2018 to February 2023. Using each asset as a benchmark to which I compared Bitcoin and Ethereum's returns, I started by performing linear regressions to determine each coin's corresponding Jensen's α. A concept developed by Jensen (1968) as a means of studying portfolio performance, Jensen's α builds on the Sharpe-Lintner (Sharpe, 1964; Lintner, 1965) capital asset pricing model (CAPM), with α measuring a portfolio or asset's excess returns beyond what is explained by the overall market returns, which are characterized by CAPM. Regressing Bitcoin and Ethereum returns against my series of benchmarks, the equation explaining each coin's return is as follows:

$$r_c = \alpha_c + [r_{ft} + \beta(r_{mt} - r_{ft})] + \varepsilon_t$$

where r_c is the rate of return on the coin at time t; r_{ft} is the risk-free rate of return, represented by continuously compounded daily return data, retrieved from WRDS, for 30-day USA Treasury bills; and r_{mt} represents the monthly return for the indexes and assets used. In this study, the Market Risk Premium, derived by subtracting r_{ft} from r_{mt}, is the return that investors would receive for investing exclusively in any of the indexes or ETFs being examined. The β coefficient is representative of either Bitcoin or Ethereum's systematic risk of being exposed to the given indexes or ETFs. If an asset has a β of 1 then movements in its return data are perfectly in step with the market index they are being compared with. Assets with a β above 1 are considered riskier than the benchmark with which they are being compared, demonstrating more exaggerated movement in their returns than the benchmark. For example, if Bitcoin maintains a 1.4 β coefficient, then a 1% return on the benchmark will result in a 1.4% return for Bitcoin. Conversely, assets with β's lower than 1 are considered less risky than the benchmark they are being compared to, demonstrating more tame return movement in response to benchmark returns. ε_t represents the error term, which encapsulates the difference between the observed results and the theoretical value of the model.

Table I.

Panel A.

	BTC	*ETH*	*S&P 500*	*S&P 350*	*HSI*
No. of obs.	62	62	62	62	62
Mean return*	0.0306	0.0551	0.0083	0.0012	-0.0056
SD	0.2240	0.3081	0.0550	0.0547	0.0676
Skewness	0.3968	0.0450	-0.3471	-0.0042	0.8218
Kurtosis	-0.3891	-0.4579	-0.1107	0.7760	3.3517

Panel B.

	SPG 1200	*URTH*	*GSCI*	*IMOEX.ME*	*GEPI*
No. of obs.	62	62	62	62	62
Mean return*	0.0042	0.0062	0.0063	0.0008	0.0114
SD	0.0514	0.0535	0.0732	0.0959	0.1078
Skewness	-0.3596	-0.3197	-2.1576	-1.0413	-0.3945
Kurtosis	0.0202	-0.0091	9.7333	2.3039	1.4549

Table 1. *Descriptive statistics for monthly excess return data from Jan 2017-Feb 2023*
**Mean returns are expressed in decimal form*

In this study, the remaining coefficient, α_c, represents the risk-adjusted abnormal return of the coin or cryptocurrency being observed – either Bitcoin or Ethereum. Based on this equation, a positive alpha indicates that the asset being observed demonstrates abnormal returns above what is predicted by CAPM. Conversely, a negative alpha indicates abnormal returns below what is predicted by CAPM. Depicted mathematically, the alpha coefficient can be isolated by rearranging the modified CAPM formula, as follows:

$$\alpha_c = r_c - [r_{ft} + \beta(r_{mt} - r_{ft})] + \varepsilon_t \qquad (1)$$

Formatted in this manner, the equation informs us that the abnormal return on the given asset is equal to the actual return of the asset minus the expected return on the market, or:

$$\alpha_c = \text{Actual Return of Crypto Asset} - \text{Expected Return on the Market/Benchmark} \qquad (2)$$

I subsequently reformat the terms to generate the following time-series regression equation:

$$r_c - r_{ft} = \alpha_c + \beta(r_{mt} - r_{ft})] + \varepsilon_t \qquad (3)$$

3.2 Momentum

While CAPM and Jensen's α are a strong basis for determining how cryptocurrencies might generally behave in relation to traditional markets, additional variables can be input into the model to potentially create a more comprehensive explanation for cryptocurrency returns. Since previous research has proposed that cryptocurrencies should be viewed as speculative assets (Carpenter, 2016; Nguyen et al., 2019), I expand my regression model to include a momentum factor. The momentum factor, a concept based on a 1993 study by Jegadeesh and Titman, posits that, in general, return performance of stocks that have done well in the past 3-12 months will remain positive, while the opposite holds true for stocks that have done performed poorly. Momentum data retrieved from WRDS is consistent with data from Kenneth French's website, which states that the momentum factor is constructed using six portfolios that include prior return data from stocks listed on the NYSE, AMEX, and NASDAQ. The resulting momentum factor is calculated using the following equation:

$$\text{MOM} = \tfrac{1}{2}(\text{Small High} + \text{Big High}) - \tfrac{1}{2}(\text{Small Low} + \text{Big Low}) \qquad (4)$$

I then use the momentum factor to modify my previous equation:

$$r_c - r_{ft} = \alpha_c + \beta(r_{mt} - r_{ft})] + \gamma MOM_t + \varepsilon_t \qquad (5)$$

3.3 Linear Regression & Correlation Tests

The previously mentioned models will be tested through linear regression using Bitcoin and Ethereum's excess returns as the dependent variable, and the momentum factor and excess returns of the selected indexes and ETFs as independent variables. Linear regressions aim to determine the degree to which changes in the independent variable(s) are capable of explaining simultaneous changes in the dependent variable. Alongside correlation tests, linear regressions will be the primary tool used to determine the strength of the relationship between the independent and dependent variables.

3.4 The Sharpe Ratio

Finally, I will examine the Sharpe Ratio to determine each cryptocurrency's potential to deliver risk-adjusted returns above and beyond those of the benchmarks used. Developed by William Sharpe (1966), the Sharpe Ratio tests for a portfolio's risk-adjusted return by dividing the portfolio's excess returns by the standard deviation of those returns. The Sharpe Ratio is represented by the following equation:

$$S_a = \frac{E[R_a - R_f]}{\sigma_a} \tag{6}$$

4. Empirical Results

4.1 Bitcoin Regressions

This section focuses on the results of the series of regressions run using Bitcoin as the dependent variable and the selected indexes and ETFs as the independent variables. The results of the regressions are indicated in Tables II. & III.

Table II. *CAPM Results for Bitcoin*

	β*	α	R^2	Obs.**
S&P 500	1.5634 (3.2214)	0.0176 (0.6564)	0.1475	62
IMOEX.ME	0.3016 (1.0088)	0.0303 (1.0667)	0.0167	62
S&P 350	1.4500 (2.9300)	0.0289 (1.0755)	0.1252	62
HSI	0.0458 (0.1072)	0.0308 (1.0712)	0.0002	62
GSCI	0.3890 (0.9924)	0.0281 (0.9842)	0.0161	62
URTH	1.6016 (3.2074)	0.0207 (0.7749)	0.1464	62
SPG 1200	1.6306 (3.1264)	0.0238 (0.8900)	0.1401	62
GEPI	0.1942 (0.7302)	0.0286 (0.9953)	0.0088	62

**T-stats are listed in parentheses*
***Data points are monthly excess returns from Jan. 2018-Feb. 2023*

Concerning the CAPM model, the r-squared, a statistical measure representing the proportion of variance in the dependent variable that can be explained by the independent variable(s), for any given index or ETF was relatively low, with the S&P500 explaining the greatest proportion of Bitcoin's variance at 14.75%. As a decentralized form of currency with no underlying basis of value, the amount of variance attributable to indexes and ETFs, which track the value of real assets or entities, is predictably low. However, the r-squared values for indexes that track the value of western countries have noticeably larger r-squared values than those of the Russian and Chinese indexes. The same principle holds true when observing the GSCI and GEPI – the commodity and energy price indexes. For the most part, r-squared values for the S&P 500, S&P Europe 350, and the global market proxies, URTH and SPG 1200, are closely related, with the S&P 350's r-squared being roughly 2% lower than the other similar indexes. Since the URTH and SPG 1200 have major exposure to U.S. markets, with URTH tracking the MSCI World Index, which maintains a 53.64% weight in U.S. based companies, and the SPG 1200 maintaining a 64.5% weighting in U.S. based companies, their r-squares are like, but lower than, that of the S&P 500. Based on the r-squared of each index or ETF, returns on U.S. equities markets have greater explanatory power for Bitcoin returns than returns on commodities or other indexes.

Similar to the r-squared results, the indexes and ETFs that were more capable of explaining variance in Bitcoin returns had greater β coefficients than their smaller r-squared counterparts. The β coefficients for the S&P 500, S&P Europe 350, URTH, and SPG 1200 ranged between 1.4-1.7, and were all statistically significant under a 95% confidence interval, indicating that Bitcoin's risk was generally much greater than that of these indexes, and that the systematic risk of these markets played a somewhat significant role in defining Bitcoin returns. Conversely, its β coefficients for the remaining indexes were much lower than one, and not statistically significant at the 95% level, indicating that Bitcoin's returns are not very responsive to returns of these indexes. Bitcoin's lowest β coefficient over the five-year period belong to HSI, the Chinese market index, with returns on the coin displaying nearly no response in relation to returns on the index.

For all the assets tested, the α_c remained consistently low, with none of the alphas obtaining statistical significance at the 95% level. The highest t-stat belonged to the HSI, at 1.0712. Thus, there was not sufficient evidence to reject the null-hypothesis H_0: $\alpha = 0$ for any of the selected assets, indicating that Bitcoin did not display abnormal returns above what was predicted by the market. However, since the r-squared for HSI, GEPI, IMOEX.ME, and GSCI were low, and they all had t-stats that were not statistically significant at the 95% level, returns on these assets do a poor job of explaining returns on Bitcoin.

Table III. *CAPM & Momentum Results for Bitcoin*

	β*	*MOM*	α	R^2	Obs.**
S&P 500	1.5985	-0.8735	0.0182	0.1787	62
	(3.3237)	(-1.4979)	(0.6876)		
IMOEX.ME	0.3301	-0.8299	0.0312	0.0448	62
	(1.1080)	(-1.3177)	(1.1037)		
S&P 350	1.4215	-0.6948	0.0296	0.1449	62
	(2.8775)	(-1.1676)	(1.1076)		
HSI	0.0931	-0.7916	0.0319	0.0257	62
	(0.2178)	(-1.2428)	(1.1144)		
GSCI	0.3612	-0.7441	0.0291	0.0388	62
	(0.9227)	(-1.1788)	(1.0213)		
URTH	1.6258	-0.8441	0.0214	0.1756	62
	(3.2834)	(-1.4457)	(0.8104)		
SPG 1200	1.6590	-0.8502	0.0246	0.1697	62
	(3.2076)	(-1.4508)	(0.9281)		
GEPI	0.1383	-0.7179	0.0299	0.0292	62
	(0.5118)	(-1.1139)	(1.0437)		

**T-stats are listed in parentheses*
***Data points are monthly excess returns from Jan. 2018-Feb. 2023*

Table III. expands on the CAPM model to include the momentum factor obtained from WRDS. Under the new model, the results remained similar to those found in the previous model. With the momentum factor being consistently negative for each asset, the α and β coefficients largely experienced sweeping, though nominal, increases, with the exception being the β coefficient for the S&P Europe 350. Similarly, r-squared also demonstrated sweeping, nominal increases, indicating that the new model was slightly more capable of explaining returns than CAPM alone. None of the t-statistics or p-values for the momentum factor indicated significance at the 95% level. Thus, Bitcoin displayed no momentum effect over the five-year period observed. This differs from Liu & Tsyvinski's 2018 study, which indicated that momentum and investor attention were important in determining returns. However, their study observed momentum at the daily and weekly levels and their momentum factor did not use data from WRDS as its basis. Instead, they generated their own momentum factors using returns on the cryptocurrencies being studied, which could explain the difference in findings.

Table IV. *CAPM Results for Ethereum*

	β*	α	R^2	Obs.**
S&P 500	2.4103	0.0351	0.1853	62
	(3.6939)	(0.9731)		
IMOEX.ME	0.3985	0.0548	0.0153	62
	(0.9686)	(1.3990)		
S&P 350	2.2340	0.0524	0.1571	62
	(3.3436)	(1.4473)		
HSI	0.4356	0.0575	0.0091	62
	(0.7439)	(1.4590)		
GSCI	0.7648	0.0502	0.0330	62
	(1.4310)	(1.2897)		
URTH	2.5092	0.0396	0.1899	62
	(3.7508)	(1.1067)		
SPG 1200	2.4985	0.0446	0.1739	62
	(3.5536)	(1.2402)		
GEPI	0.4033	0.0505	0.0199	62
	(1.1040)	(1.2847)		

**T-stats are listed in parentheses*

***Data points are monthly excess returns from Jan. 2018-Feb. 2023*

Ethereum's regression results under the CAPM model remained consistent with those demonstrated under Bitcoin's CAPM regression. Ethereum's r-squared values were somewhat higher than those exhibited by Bitcoin, with the highest reaching almost 0.19. While the difference in their values was small, URTH demonstrated a greater r-squared over the period than the S&P 500. This deviation from Bitcoin, suggests that there may be market factors outside of the U.S. capable of explaining Ethereum returns. However, since the other global indexes' SPG 1200, r-squared remained comfortably below the S&P 500's, it is unclear what exactly that factor could be. The difference is so small so I conjecture that it is likely due to chance and that by varying the period being observed, we may see the S&P 500's r-squared overtaking URTH. With the exception of HSI, whose β is lower than it was for Bitcoin, the β coefficients for

Ethereum appear to be exaggerated variants of their Bitcoin counterparts. As it was under the CAPM model for Bitcoin, the U.S., European, and global indexes maintain high betas for Ethereum. Ethereum's beta range for the S&P 500, S&P Europe 350, URTH, and SPG 1200 starts as low as 2.23 and caps out just shy of 2.51. Although Bitcoin already maintained high betas, within the 1.4-1.7 range, Ethereum's beta data shows that it is much riskier than Bitcoin. Consistent with Bitcoin, the indexes and ETFs for which Ethereum has high betas maintain high t-stats that demonstrate statistical significance at at least the 95% level, indicating that factors influencing the returns on these proxies are somewhat capable of defining Ethereum's returns, as well. In keeping with the trend of being an exaggerated version of Bitcoin, the returns attributable to Ethereum's α for any given index were comparably higher than those linked to Bitcoin. However, each of Ethereum's α's was not statistically significant at the 95% level. Thus, like Bitcoin, none of Ethereum's α*'s* could reject the null hypothesis, H_0: $\alpha = 0$, indicating that any and all overperformance observed was simply due to chance.

With the selected indexes and ETFs maintaining low r-squared values for Ethereum, they struggle explain a majority of Ethereum's returns. Similar to Bitcoin, IMOEX.ME, HSI, GSCI, and GEPI's r-squared values for Ethereum were lower relative to the proxies for western and global markets, with each capable of explaining less than 5% of the variance of returns for Ethereum. Coupled with a lack of statistical significance for their respective β coefficients, each of these assets does an extremely poor job of explaining Ethereum's returns.

Table V. *CAPM & Momentum Results for Ethereum*

	β*	*MOM*	α	R^2	Obs.**
S&P 500	2.4622	-1.2924	0.0360	0.2214	62
	(3.8232)	(-1.6550)	(1.0140)		
IMOEX.ME	0.3635	-1.8010	0.0652	0.0632	62
	(0.7909)	(-1.7301)	(1.5222)		
S&P 350	2.1923	-1.0169	0.0536	0.1794	62
	(3.2939)	(-1.2684)	(1.4859)		
HSI	0.5081	-1.2145	0.0592	0.0409	62
	(0.8711)	(-1.3974)	(1.5136)		
GSCI	0.7246	-1.0767	0.0516	0.0581	62
	(1.3597)	(-1.2528)	(1.3317)		
URTH	2.5451	-1.2487	0.0407	0.2237	62
	(3.8515)	(-1.6025)	(1.1526)		
SPG1200	2.5403	-1.2559	0.0458	0.2080	62
	(3.6567)	(-1.5953)	(1.2889)		
GEPI	0.3265	-1.0024	0.0528	0.0412	62
	(0.8841)	(-1.1379)	(1.3469)		

**T-stats are listed in parentheses*

***Data points are monthly excess returns from Jan. 2018-Feb. 2023*

In table V., I report the results of the Ethereum multifactor regression, using the selected indexes and ETFs, and the momentum factor as independent variables. While including the momentum factor when regressing for Bitcoin increased nearly all betas, it had mixed results on Ethereum betas. However, the general results remained consistent with Ethereum's CAPM regression, with the proxies for western and global markets demonstrating greater r-squared and higher betas than the proxies for commodities and eastern markets. Furthermore, the S&P 500, S&P 350, URTH, and SPG 1200 continued to exhibit β coefficients signaling their significance under a 95% confidence interval. As was the case with Bitcoin, Ethereum's t-stats for all α coefficients and the momentum factor maintained a lack of statistical significance at the 95% level. Therefore, I am unable to reject the null hypotheses H_0: $\alpha = 0$ and H_0: $MOM = 0$, indicating that any over- or under-performance attributed to α occurred by chance, and that momentum had no effect on returns over the period.

4.2 Correlations

While investment goals and strategies vary by investor, diversification, or the act of spreading out return exposure across a variety asset classes or assets, is an important tool for limiting potential losses and bolstering overall portfolio return. Thus, I further investigate Bitcoin and Ethereum's correlation coefficients, a statistical measure that dictates how two variables – in this case returns – move in relation to each other, with my selected assets to better determine cryptocurrency's potential as a diversification tool. The value of the correlation coefficient ranges from -1.0 to 1.0, with a coefficient of -1.0 signifying perfect negative correlation and a coefficient of 1.0 representing perfect positive correlation. If two variables are perfectly negatively correlated, when one variable increases the other experiences a decrease of the exact same magnitude. Conversely, if two variables are perfectly positively correlated, when one variable increases the other experiences an increase of the exact same magnitude. To achieve more consistent overall returns through diversification, investors look for assets that are negatively correlated.

Table VI. *Bitcoin Correlations*

Asset	6 Months	1 Year	3 Years	5 Years
ETH	0.9065	0.8813	0.7401	0.7166
S&P500	0.3699	0.6038	0.5995	0.3840
IMOEX.ME	0.5403	-0.3057	0.1936	0.1292
S&P 350	0.2052	0.5622	0.4880	0.3538
HSI	-0.0809	-0.1553	0.1067	0.0138
GSCI	-0.3609	0.3359	0.1519	0.1271
URTH	0.3562	0.6092	0.5906	0.3826
SPG1200	0.3086	0.5797	0.5701	0.3743
GEPI	-0.5022	-0.1864	0.1298	0.0935

Correlation coefficients are generated using monthly return data dated back 6 months, 1 year, 3 years, & 5 years from February 2023 to January 2018

In table VI. I report the correlation coefficients between Bitcoin and all other assets being studied across varying time periods, from as little as six months to just over five years. The objective of assessing multiple time periods was to test the validity of traditional media's assertions that cryptocurrencies' correlation to traditional markets has progressively become stronger and more positive over time. Predictably, Bitcoin returns were highly correlated with Ethereum returns, as they both operate and compete on the same fundamental level. In keeping with the statements that Bitcoin has become increasingly correlated with traditional markets over time, Bitcoin's correlations with the returns on indexes for western countries and global markets increased as the time observed decreased, only deviating from this trend when considering the 6-month correlations. However, with monthly data being used as the basis for correlation, the 6-month correlation may not have a sufficient sample size to appropriately characterize the correlation coefficient over the period. Since the correlation coefficients for the western and global indexes seem to move relatively in step with each other, I tested the daily 6-month correlation coefficient for Bitcoin and the S&P 500, which returned 0.52 – a much more moderate decrease than the monthly correlation coefficients suggested. However, some of Bitcoin's daily returns were omitted from the sample, due to stock markets being closed on weekends and holidays.

The correlation coefficients for the remaining indexes and ETFs did not seem to move in patterns similar to the proxies for western and global markets. The Bitcoin-HSI correlation coefficient was the most stable, exhibiting a low positive correlation over the 3- and 5-year periods and low negative correlations over the 6-months and 1-year periods. GEPI and GSCI displayed similar results. However, their 6-month correlation coefficients were much more strongly negatively correlated with Bitcoin than the HSI. Finally, IMOEX.ME displayed low positive correlations for the 3- and 5-year tests, a negative coefficient for the 1-year test, and then dramatically shifted to a moderately large positive correlation under the 6-month test. Since the change in correlation for IMOEX.ME was so dramatic, I performed a 6-month correlation test using daily returns, which yielded a correlation coefficient of 0.062.

Taken at face value, the results in Table VI., and the separate correlation tests, indicate that Bitcoin returns are moving more in step with the returns on the proxies for western countries and global markets, but not with returns on the Russian, Chinese, and commodities indexes.

Table VII. *Ethereum Correlations*

Asset	6 Months	1 Year	3 Years	5 Years
BTC	0.9065	0.8813	0.7401	0.7166
S&P500	0.6121	0.7281	0.6690	0.4304
IMOEX.ME	0.6857	-0.2604	0.1840	0.1241
S&P 350	0.4049	0.5782	0.5057	0.3963
HSI	-0.1832	-0.2581	0.0958	0.0956
GSCI	-0.3190	0.3586	0.1173	0.1817
URTH	0.5615	0.7017	0.6537	0.4368
SPG1200	0.5128	0.6637	0.6146	0.4170
GEPI	-0.6618	-0.0656	0.1304	0.1411

Correlation coefficients are generated using monthly return data dated back 6 months, 1 year, 3 years, & 5 years from February 2023 to January 2018

Table VII. reports correlation data between Ethereum and the selected assets over varying time periods, with six months referring to the correlation based on monthly price data for the last six months from February 2023, 1 year referring to the past 12 months from February 2023, and so on. Volatility in correlation coefficients was most prominent with the commodities, energy, and Russian market indexes. Since the IMOEX.ME exhibited such a dramatic change from 1-year to 6-months, I used daily data to perform an additional correlation test for the 6-month IMOEX.ME correlation coefficient, which returned much lower at 0.04. HSI, the Chinese market index, displayed very small positive to negative correlations with Ethereum over the time selected periods. Ethereum returns were more highly correlated with the S&P 500, global market indexes, and, to a lesser extent, the S&P Europe 350. While the results of the correlation tests seemingly affirm the news from traditional media outlets that cryptocurrency returns have begun to move increasingly in step with returns on traditional assets — specifically for indexes with majority holdings in western countries — the correlation results for my 6-month period resulted in more moderate positive correlation than the 1-year test. Additionally, when testing Ethereum's correlation against daily S&P 500 returns a 6-month period, I found the correlation coefficient to be 0.09 – far less than the value received when using the monthly returns. However, cryptocurrencies are volatile assets and daily data may cause too much variation in returns to develop a meaningful correlation coefficient that accurately represents overall long-term returns. Ultimately, it is difficult to find a balance between an appropriate sample size and data that is too "noisy" to form any concrete interpretations on.

4.3 Sharpe Ratio

Pulling mean and standard deviation data from my descriptive statistics, I calculate the Sharpe ratio for Bitcoin, Ethereum, and the selected indexes and ETFs. The results of these calculations are presented in Table VIII.

Table VIII. Sharpe Ratios

Asset	Mean of Monthly Excess Returns	STDev*	Sharpe Ratio**
S&P 500	0.83%	5.50%	0.151
IMOEX.ME	0.08%	9.59%	0.008
S&P 350	0.12%	5.47%	0.022
HSI	-0.56%	6.76%	-0.082
GSCI	0.63%	7.32%	0.087
URTH	0.62%	5.35%	0.116
SPG 1200	0.42%	5.14%	0.081
GEPI	1.14%	10.78%	0.106
BTC	3.06%	22.40%	0.136
ETH	5.51%	30.81%	0.179

**Standard deviations are based on monthly returns and expressed in the same units as excess returns*
***The Sharpe Ratio is calculated as the quotient of Mean Excess Returns and STDev*

Comparing the Sharpe ratios across all the selected assets, Bitcoin and Ethereum demonstrate risk-adjusted returns that overshadowed those of the remaining assets, with Ethereum exhibiting the highest Sharpe ratio overall. As a risk-adjusted measure, the Sharpe ratio accounts for standard deviations in excess returns and weighs them against the returns themselves. Although Bitcoin and Ethereum maintained much higher average monthly excess returns, their high standard deviations, or risk, largely mitigated any overperformance relative to the benchmarks with the highest Sharpe ratios.

5. Discussion

Ultimately, the objective of this paper is to examine cryptocurrency's viability as an investment opportunity. Taking their legitimacy and liquidity as a given, the two dimensions through which I examined their viability are the strength of their relationship with traditional investment opportunities and their risk-adjusted return. Based on the regression tests, I determined that the excess returns on western and global proxies were capable of explaining a sizeable portion of returns on either Bitcoin or Ethereum, with the beta coefficient, or systematic risk, carrying the bulk of the explanatory power. While the regressions between the selected cryptocurrencies and the indexes and ETFs tracking western and global markets maintained betas that were statistically significant, their low r-squared values indicate that there were also other variables, not included in the model, that were more capable of explaining cryptocurrency returns. Meanwhile, the returns on proxies for commodities, energy, Russian, and Chinese markets, demonstrated poor explanatory power for cryptocurrency returns. Due to a weak relationship between energy prices and Bitcoin and Ethereum returns, I am skeptical of the assertions of Hayes' 2017 study that energy prices may be a major driver behind cryptocurrency value formation.

For the purposes of this paper, I assumed that the risk-free rate for all traders was the return on a U.S. one month treasury bill. However, if alternative risk-free rates were to be used, then the results of the study would differ, with the magnitude of the difference depending on the rate selected. Moreover, the study also utilized monthly return data and observed a five-year period. While monthly return data likely presents a clearer, less “noisy” picture for characterizing Bitcoin and Ethereum returns than daily return data, I acknowledge that changing the frequency of returns utilized could yield a more or less appropriate representation of returns overall and result in dramatic deviations from the findings of this paper. Furthermore, expanding the study period to incorporate more than five-years’ worth of data will yield greater insights into the relationships of the selected assets and cryptocurrencies.

Regarding the data itself, it may be beneficial to expand the number of market economies and coins observed. While the U.S., Europe, and China are major components of the world economy, the number of individual countries observed in the study is limited. Moreover, Bitcoin and Ethereum are the two largest cryptocurrencies available. Analyzing mid- or small-cap cryptocurrency returns or returns on a cryptocurrency ETF may be more representative of cryptocurrency performance over a period. However, liquidity and legitimacy of the coins must be considered as returns cannot be realized in the absence of these two factors.

The final component of my regressions, the momentum factor, is generated utilizing data from U.S. indexes. If I had access to momentum factors for other market economies, or the expertise to generate the factors myself, my regressions would likely have been more accurate for each given asset. Additionally, I could have emulated Liu & Tsyvinski’s 2018 study to establish a momentum factor based on the returns of the coins themselves, which may have been a more appropriate approach to creating a more comprehensive model. Thus, for future research, I encourage the analysis of a greater number of market economies, and more current and appropriate analysis of momentum factors to better characterize regression outputs. An additional consideration would be to observe return data through the lens of key macro events, such as Russia’s invasion of Ukraine, the COVID-19 Pandemic, the high inflationary period that plagued the U.S. in 2022 into 2023, and China's ban of cryptocurrencies, or any event that may have significant impacts on a given economy or cryptocurrency.

The correlation coefficient tests expanded further upon the regressions' objective of determining the relationship between cryptocurrencies and traditional asset classes. While the resulting correlation coefficients indicate that cryptocurrencies are moving more in line with western and global markets, they demonstrated weak or mixed correlations with the remaining assets observed. However, low sample sizes, particularly for the six-month correlation tests may have resulted in inaccurate outcomes. Assuming the validity of the results presented in Tables VI. & VII., returns on Bitcoin and Ethereum have steadily grown stronger and more positively correlated with returns on proxies for western and global markets. This development suggests that cryptocurrencies may be a poor source of diversification if investing directly in these market indexes. It is worth noting that these correlation coefficients are for proxies of these markets and not the individual assets within them. Therefore, cryptocurrencies may still be capable of serving as a diversification opportunity for individual assets but not these markets at large. On the other hand, the low positive or even negative correlations, along with extremely low r-squared values, suggest that Bitcoin and Ethereum may present reasonable diversification opportunities for the remaining indexes.

The second component of investment viability, the risk-adjusted returns of Bitcoin and Ethereum, relative to those of the selected assets, is characterized by their Sharpe ratios. While Ethereum demonstrated the highest Sharpe ratio of the assets observed, it is important to note that the standard deviation of its returns was just over 30%. Although the Sharpe ratio adjusts returns based on risk, some investors may find it to be too volatile to consider as an investment opportunity. This principle undoubtedly applies to Bitcoin as well, as its standard deviation was over 22%. Thus, while Bitcoin and Ethereum exhibit some of the greatest Sharpe ratios of the assets observed, their comparatively large standard deviations leave me in agreement with the results of Petukhina et al.'s 2021 study, where they state that considering the risk-profile of the investor is imperative in determining a cryptocurrency's viability as an investment. Like all other measures in this study, the Sharpe ratio is calculated using monthly returns. Future research could look to annualize returns and standard deviations to find the Sharpe ratio on an annual basis. Moreover, my paper uses only one asset as the basis for each Sharpe ratio. Although the Sharpe ratio is a historical measure, blended portfolios, or portfolios containing traditional assets and cryptocurrencies, could be created and observed to determine if a given proportion of traditional assets and cryptocurrencies may consistently offer greater risk-adjusted returns.

6. Conclusion

Observing monthly return data on cryptocurrencies and traditional markets over a five-year period, I determined that the returns on selected proxies for Russian, Chinese, global, and commodities markets were unable to adequately explain the returns on Bitcoin and Ethereum. On the other hand, returns on proxies for western and global markets were capable of explaining a sizeable amount of returns on Bitcoin and Ethereum**.** While the regressions on western and global markets had high r-squared values relative to the remaining assets observed, their overall r-squared values were never above 0.20 for Bitcoin or Ethereum, implying that there are factors outside of those influencing traditional markets that affect Bitcoin and Ethereum returns. This indicates that the CAPM is a somewhat useful tool for characterizing Bitcoin and Ethereum returns, and perhaps cryptocurrency returns at large. Adding the momentum factor to my model barely changed r-squared values, suggesting that the momentum factor utilized had little effect on defining Bitcoin and Ethereum's returns.

Taken on a monthly basis, my observed correlation coefficients suggest that traditional media outlets were correct in stating that Bitcoin and Ethereum are beginning to move more in step with the stock market, with the caveat being that the markets in question are global markets, which have a major exposure to western markets, and western markets themselves. Bitcoin and Ethereum either maintained low positive to negative correlations with the remaining assets observed.

Finally, the Sharpe ratios derived from my data indicated that Bitcoin and Ethereum's risk-adjusted returns were some of the highest among the assets observed. Accompanying these high Sharpe ratios were higher than average excess returns and much higher standard deviations within those returns. In essence, I affirm the riskiness of cryptocurrencies as an investment vehicle.

Taking all my results into consideration, I am unable to make any definitive conclusions on the role cryptocurrencies will play in influencing the future of finance. While they can potentially be mixed with individual assets that maintain low correlations with their returns as a means of diversification, that is beyond the scope of this paper. Assessing their viability as an investment through the lens of diversification and risk-adjusted return, they seem best suited for passive, risk-seeking investors who maintain investments in non-western market proxies.

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