Bitcoin Analysis as an Alternative Asset Class

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Abstract

As cryptocurrencies grow in monetary value, so does the need for a knowledge base around how to treat them as financial assets. Cryptocurrencies are rapidly evolving in the public eye which makes them appear unpredictable compared to traditional investment assets. We propose that an ability to fit cryptocurrencies into a new paradigm with an existing knowledge base would allow investors increased opportunities for financial gain. The prior work done in this field has attempted to find connections with cryptocurrencies and asset classes but lacks up to date data sets and focuses too closely on Bitcoin in particular, rather than a variety of cryptocurrencies. Our approach is to replicate these previous studies with more up-to-date data as well as expand the analyses to multiple cryptocurrencies. We found that in the last 2 years, cryptocurrencies have become strongly correlated with the technology sector of the stock market and that the correlation has been increasing over time. These findings suggest that knowledge about deviations in the technology sector could be applied to the cryptocurrency markets as well and thus opening more opportunities for high return investments.

1 Introduction

1.1 Motivation

Blockchain and cryptocurrencies are growing rapidly in implementation, public support, and societal trust. With the expanding domain of problems which can be automated and decentralized through blockchain applications comes new opportunities for economic growth. These opportunities, however, come with high levels of risk due to the limited understanding of what causes price fluctuations in cryptocurrencies. There currently exists extensive investment knowledge based on stock markets and their sectors within. Extensive research on stock markets, bond markets, commodity markets, and derivatives markets and their respective sub sectors already exists. We seek to find correlations between cryptocurrencies and existing stocks, Exchange-Traded Funds (ETFs), and market sectors in order to apply the existing knowledge to include cryptocurrencies in investment portfolios. Finding investment assets which correlate with cryptocurrency prices allows for a better understanding of when their prices may change. Increasing the ability to predict price changes creates obvious opportunities for investors to maximize investment returns.

1.2 Related and prior work

The previous research has shown a strong focus on the technical opportunities presented by Bitcoin and the blockchain technology. While these technical details are important in solidifying the validity of cryptocurrencies, there is a gap in knowledge around the impact of valid cryptocurrencies on our culture, society, and markets. Furthermore there are differing views on the most important facets of the blockchain technology being either a payment platform or an effective currency [1]. We suspect that the rise of cryptocurrencies will have significant impact on our economy by providing new investment opportunities, regardless of their specific use cases. It has been shown previously that investing in Bitcoin may be an excellent way to provide diversity in a portfolio [2, 5], as a hedge against global uncertainty [3], or as a speculative investment [4]. However, relevant research lacks up to date data on Bitcoin as it matures. Additionally, hundreds of new cryptocurrencies with rapid growth opportunities such as Ethereum and Litecoin have come into existence since similar research was done. The quickly growing nature of these technologies gives added importance to having the most up-to-date data possible and diminishes the value of aging research.

1.3 Proposed Work

Our research interest lies primarily in determining correlations between cryptocurrencies such as Bitcoin, Ethereum, and Litecoin and other generic or marketable securities, such as stocks, bonds and gold. To that end, our goals include updating existing prediction models with the more up to date cryptocurrency datasets now available and finding patterns within the trade behavior of cryptocurrencies and other investments.

In this paper we provided up-to-date answers to the following questions:

- Have cryptocurrencies become more stable over the last few years?
- Do newer cryptocurrencies show similar trends to Bitcoin?
- Is Bitcoin a good hedge against stocks?
- Does the price of cryptocurrencies accurately reflect their real value?
- How are cryptocurrency prices related to foreign market indices?
- How risky are cryptocurrencies investments compared to more traditional investment strategies?
- Given the risks associated with different cryptocurrencies, which cryptocurrency is the best investment?

2 Methodology

2.1 Problem Formulation

Cryptocurrencies play a mysterious role in the world of finance and investment due to their complex innerworkings, user anonymity, and lack of general public trust. Nonetheless, they have increased in value exponentially in the last few years. This presents an opportunity for superb return on investments and wealth growth. Investors, however, remain wary because of the unpredictability of the new technology. To give investors an improved understanding of risk, returns, and fluctuations of cryptocurrencies we must draw lines between cryptocurrencies and known investment options. These lines provide a guide for what to expect and how to invest in cryptocurrencies.

2.2 Datasets

We have utilized historical price data representing three cryptocurrencies, three ETFs, gold, Chicago Board Options Exchange Volatility Index (VIX), and several foreign markets. The cryptocurrencies chosen were Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC). They were selected because of their overall prevalence as well as market capitalization value. Because Ethereum and Litecoin are relatively new, we have limited data for them. Data from 2013 to the present is used for analyses involving Bitcoin.

The ETFs selected were Vanguard Information Technology ETF (VGT), Vanguard S&P 500 ETF (VOO), and Vanguard Total Stock Market ETF (VTI). VGT invests in information technology stocks. VTI invests in stocks across the entire stock market. And, VOO invests in S&P 500 stocks. We picked these because they are a holistic measure of how cryptocurrencies track different market sectors. Historical price data is available for these three ETFs going back to 2009. Only the subset of this data for which there was a corresponding value in the cryptocurrency dataset was used in the following analyses.

Gold is considered a traditional hedge against inflation as the amount of gold in the world is a fixed and finite quantity for most practical purposes [11]. In a low interest rate environment the return on savings will be lower and economic theory expects people to spend money rather than save it. As more people spend money, the price of goods is expected to rise as an increase in demand makes goods scarcer. This increase in the price of goods is known as inflation and is essentially the erosion of spending power. For people who choose to save, the only option is to seek out riskier or more volatile investments which have higher returns, such as cryptocurrencies.

The VIX is an index of expected volatility in the S&P 500 using option contract prices [13]. The VIX is designed to be inversely correlated with the S&P 500 and the index is used to determine the price of VIX futures contracts to hedge against a decline in the S&P 500. Also known as the “Fear Index”, we are using the VIX as a proxy measure of investor expectations of volatility risk.

The foreign markets included in our analysis include the United Kingdom - London Stock Exchange FTSE 100, Japan - Nikkei 225, Russia - Russian Trading System (RTS) Index, and Hong Kong (China) - Hang Seng Index (HSI). Our interest in these market indices is primarily if behavior witnessed in these markets was similar to behavior in United States markets. In each instance, the index is a market capitalization-weighted index of 100, 225, 50, and 50 largest companies respectively. The Hang Seng Index has significant exposure to Chinese companies while lacking the volatility and uncertain oversight of the Shanghai Exchange [12].

2.3 Preprocessing

After obtaining the datasets, they had to be reformatted to be consistent across sources. For the cryptocurrencies and US stocks, this required that they be reordered and the dates reformatted to be quickly read and compared through our code. The main data processing issues arose from the frequency in which data is reported. Because cryptocurrency prices are reported every day and stocks are only reported on business days, their records do not match up evenly. To overcome this issue, we wrote a script that, when given two assets and a start and stop date, would return the asset prices on days that both assets were reported and were between the two given dates.

For foreign indices, we took the additional step of converting the index to United States Dollars (USD). How easily this was accomplished depended on the availability of data. For instance, the Great Britain Pound/USD exchange rate data was only available on a monthly basis, while the Japanese Yen/USD was available on a daily basis. In the instance of Hong Kong, the Hong Kong Dollar (HKD) is pegged to the USD at a rate of 7.75-7.85 HKD to the USD since 2001. The Moscow Exchange RTS Index is already denominated in USD.

2.4 Design

Our experiment will take the price data from the three cryptocurrencies and make assessments on how they relate to current US and foreign stocks as well as their levels of risk and volatility.

We compare our cryptocurrencies to stocks, commodities, and foreign indices by using the Pearson correlation coefficient. Through this method we are able to see to what degree the stock and cryptocurrency prices rise and fall together.

Our risk analysis considers the standard deviation across the opening and closing price values for various ETFs, cryptocurrencies, and foreign market indices. Using these standard deviations, we are able to compute a volatility index which allows us to compare the associated risks of these different investments.

Our risk-based returns investment analysis uses the downside deviation across the opening and closing price values for the various ETFs and cryptocurrencies as well as the average returns of the ETFs and cryptocurrencies. The downside deviation is the square root of the semivariance: variance composed only of observations that are below the mean [18]. Based on these, we can use the Sortino Ratio to calculate the best cryptocurrency to invest in.

2.5 Implementation

Our experiment was implemented primarily through python and relied on the matplotlib, numpy, and pandas packages. The price data from each asset was cleaned and saved in its own file. From the set of clean files we were able to extract the needed information to make the proper comparisons.

3 Evaluations

3.1 Setup

The main evaluation techniques focus on testing ways in which cryptocurrencies could help investors grow and improve their investment portfolios. We setup our study to first examine the correlation between US markets and cryptocurrencies to establish a baseline of understanding for how cryptocurrencies behave relative to the financial climate they are in. In attempt to widen the applicable areas of our results we then expand our knowledge to markets around the world.

Knowing the correlation between markets and cryptocurrencies, we move to further our understanding of the impacts of cryptocurrencies on investment portfolios. We gauge this through their risk levels and expected returns.

3.2 Results

i. Intra-crypto correlations.

Cryptocurrencies display a high degree of correlation with each other. Table 3.1 shows the correlation coefficients between Bitcoin, Ethereum and Litecoin. The high levels of correlation here suggest that their values come from an overall societal trust or understanding of cryptocurrencies, rather than independent features. This would also suggest that since Bitcoin is the most popular, anything that affects the public opinion of Bitcoin will spill over to the public opinion of all cryptocurrencies. This effect can be seen in the high correlation between cryptocurrencies as well as in Figure 3.1.

Asset	Bitcoin	Ethereum	Litecoin
Bitcoin	1	0.97	0.95
Ethereum		1	0.95
Litecoin			1

Table 3.1: Correlation Coefficients between Cryptocurrencies

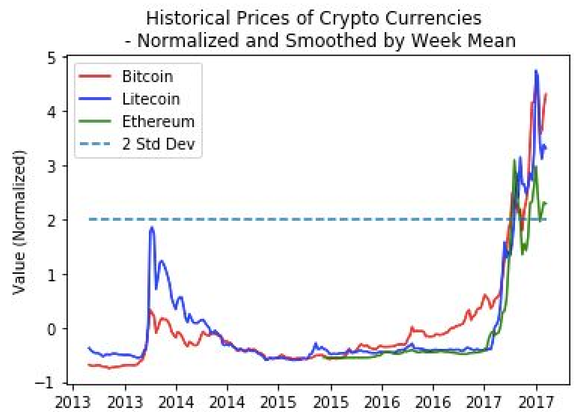

Figure 3.1: Cryptocurrency Historical Behavior

ii. Stock-Cryptocurrency Correlations

We found that, unlike the previous research, there exists a significant and growing correlation between the selected cryptocurrencies and ETFs. Table 3.2 shows that our selected cryptocurrencies are most correlated with VGT, the technology based ETF. This result means that investors should treat investments into cryptocurrencies similar to technology investments. The price of cryptocurrencies is likely to fall as the technology sector falls and rise as the technology sector rises. This is also contrary to existing research which placed cryptocurrencies as an excellent opportunity for portfolio diversification. We can see from Figure 3.2 that Bitcoin and VGT peak in prices at the same time. The curve in the graph suggests that when both assets are growing towards their highest levels, Bitcoin grows much faster. It is for this reason that investors should be interested in cryptocurrencies. Even though they mimic trends within traditional stocks, they often have dramatic upswings in price.

	VGT	VTI	VOO
Bitcoin	0.75	0.7	0.7
Ethereum	0.79	0.73	0.74
Litecoin	0.51	0.45	0.44

Table 3.2: Correlation Coefficients between Cryptocurrencies and various ETFs - all years.

Additionally, Figure 3.4 shows that the correlation between cryptocurrencies and the technology sector has moved from negative to positive in the recent years. The negative correlation in 2014 comes during a significant crash as seen in Figure 2.4. This suggests that cryptocurrency price fluctuations had little to no effect on the stock market and the cause of the crash was not important to stock market investors. However, there has been a shift in how investors see cryptocurrencies in the last few years. The issues which were driving prices within the technology sector are becoming more important to the investors holding cryptocurrencies.

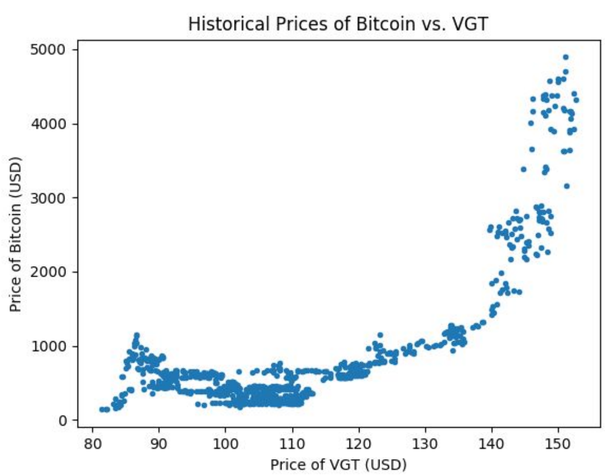

Figure 3.2: Scatter plot of VGT and BTC prices in last 3 years.

Year/Asset	Bitcoin	Ethereum	Litecoin
2013	0.77	N/A	0.64
2014	-0.64	N/A	-0.82
2015	0.44	-0.09	0.10
2016	0.79	0.45	0.33
2017	0.88	0.86	0.89

Table 3.3: Correlation with VGT in the last 5 years.

ii. Crypto correlations across Foreign Markets

In this section, we give correlation values across cryptocurrencies and foreign market indices. We found there to be a varying level of correlation between the foreign markets we considered and cryptocurrencies. We consider the following foreign exchange in this section: Russia's RTS [6], England's FTSE [8], Hong Kong's Hang Seng [14], and Japan's Nikkei [9]. We considered these Markets during similar timeframes as to when we considered the cryptocurrencies. For example, for the RTS, we considered a date range 9/2013 until around 08/2017, similar to the dates we have for cryptocurrencies.

While there is a positive correlation between cryptocurrencies and the HSI and Nikkei indices, a very small correlation with the RST index, and an overall negative correlation between cryptos and the FTSE Index. Further research is necessary to explain the results of the correlation with the FTSE. The correlations diverged in 2015, which was prior to the Brexit referendum. These results suggest that investors should pay special attention to which markets they have exposure to when adding cryptocurrencies to their portfolios. Cryptocurrencies could play different roles within a portfolio based on the market the portfolio is most exposed to. For a United Kingdom investor, the negative correlation suggests that cryptocurrencies would provide an opportunity for diversification and hedging. Conversely, an investor in Hong Kong or Japan would not find the same value in cryptocurrencies because their prices are expected to move similarly to the rest of the market.

Index/Asset	Bitcoin	Ethereum	Litecoin
FTSE 100	-0.28	0.19	-0.05
HSI	0.51	0.80	0.47
RTS	0.02	0.38	0.16
Nikkei 225	0.69	0.73	0.50

Table 3.4: Correlation Coefficients of Closing Prices between various Foreign Indices and Cryptocurrencies

iii. Risk

In an effort to measure risk, we first measured the standard deviations across certain attributes of each asset class. We choose to consider the open, close, high, low and volume values. Tables 3.5 and 3.6 show these values.

	Open	High	Low	Close	Volume
VGT	25.47	25.53	25.40	25.48	238,328
VTI	20.22	20.22	20.21	20.22	1,572,013
VOO	36.11	36.13	36.13	36.13	1,173,414

Table 3.5: Standard Deviation values across ETFs.

	Open	High	Low	Close	Volume
BTC	841.31	870.48	812.59	845.90	513,760,575
ETH	102.81	107.17	97.86	103.13	427,838,338
LTC	13.10	13.84	12.27	13.14	149,422,751

Table 3.6: Standard Deviation values across cryptocurrencies.

	Open	High	Low	Close	Volume
RTS	201.23	200.75	201.88	201.41	320,444,553
FTSE[1]	N/A	N/A	N/A	587	N/A
Nikkei[2]	18.46	18.42	18.54	18.51	59,612
HSI[3]	344.18	343.86	342.99	343.46	589,712,832

Table 3.7: Standard Deviation Across Foreign Markets.

We then calculate a volatility index of each asset we are considering. The volatility index, ∂, is defined as:

$$\partial = \left|\sigma(Open_i) - \sigma(Close_i)\right|$$

where i is an asset class and σ is the standard deviation. A higher index represents a higher historical tendency for dramatic price

[1] Our FTSE data set did not include Open, High, Low, and Volume data values

[2] Values were converted to USD from JPY Yen using an exchange rate of (1 JPY = 0.0089 USD).

[3] Values were converted to USD from HSD using an exchange rate of (1 HKD = 0.13 USD).

movements within an index. Table 3.8 shows our findings for this measure.

VGT	0.01103
VTI	0.00510
VOO	0.01541
Bitcoin	4.5974
Ethereum	0.31476
Litecoin	0.04232
RTS	0.65
FTSE	N/A
Nikkei	0.05
HSI	0.72

Table 3.8: Volatility indices across considered cryptocurrencies, ETFs, and Foreign Exchange.

These results were somewhat surprising. Ethereum and Litecoin were both less volatile than both the RTS and HSI during this period we considered. Bitcoin, however, had a volatility magnitudes greater than everything else. We attribute this to Bitcoin being more popular, thus having investors willing to buy and sell Bitcoin on a whim. Ethereum and Litecoin are not as well known, as thus arguably have more stable investors who invest on the technological merits of the cryptocurrencies and not in the hopes of quicky cashing out their gains.

iv. Risk-Adjusted Returns.

We can calculate the risk-adjusted return for each cryptocurrency to find which have the highest return per unit of risk. To do so, we will use the Sortino Ratio which is a measure of risk-adjusted return [17]. The ratio uses the square root of semivariance (downside deviation) of a data set its risk measure instead of standard deviation. Semivariance only includes observations below the mean and therefore only measures negative volatility [18]. Traditional variance measures all volatility, including positive volatility, which is generally beneficial to investors.

The higher the Sortino Ratio, the better the investment is. Table 3.9 shows the Sortino Ratio and average return per unit of risk for each cryptocurrency while Table 3.10 shows the Sortino Ratio and average return per unit of risk for each ETF.

	Avg Returns	Sortino Ratio
BTC	718.8	0.9940
ETH	58.63	0.9851
LTC	9.33	0.9849

Table 3.9: Average Returns and Sortino Ratio values across cryptocurrencies.

	Avg Returns	Sortino Ratio
VGT	107.09	1.1291
VOO	187.2227	1.1292
VTI	105.2347	1.1292

Table 3.10: Average Returns and Sortino Ratio values across ETFs.

From these results, Bitcoin as an asset provides the highest average return while also having the highest Sortino Ratio among cryptocurrencies. With Bitcoin's high average return, there is a significant downside risk which could translate into significant losses for an investor. Also, our results show that the while all stock market ETFs have extremely close ratios, the VOO will provide the highest average returns between them. These results indicate that, adjusted for risk, a traditional ETF investment is generally superior to a cryptocurrency investment despite the dramatic upside potential of cryptocurrencies due to having the highest ratio between the cryptocurrencies and the ETFs.

iv. Non-stock assets.

With gold, our expectation was to see a strong positive correlation given the low-interest rate environment making up the majority of the past decade. Surprisingly, the correlation was quite weak except in the case of Ethereum. This implies that the search for yield took priority over inflation concerns, which is visible in the data on Table 3.11 for most periods.

	Bitcoin	Ethereum	Litecoin
Gold	0.125	0.328	0.165
Gold 2013	-0.570	N/A	-0.515
Gold 2014	0.433	N/A	0.393
Gold 2015	-0.660	-0.161	-0.682
Gold 2016	0.221	0.735	0.400
Gold 2017	0.751	0.641	0.667

Table 3.11: Correlation Coefficients between cryptocurrencies and gold.

Correlations between cryptocurrencies and the VIX were consistently negative. Given the high correlation between cryptocurrencies and ETFs and the expected negative correlation between the VIX and ETFs, this reinforces our findings that cryptocurrencies are no longer an effective hedge against stock market volatility.

	Bitcoin	Ethereum	Litecoin
VIX	-0.388	-0.441	-0.351

Table 3.12: Correlation Coefficients between cryptocurrencies and the VIX.

4 Discussion

The new knowledge generated in this paper has real world applications for investors looking to grow their portfolios. The insights about increasing correlation between cryptocurrencies and the technology sector of the stock market provides a framework with which investors can make better informed speculative investments.

We also present measurements of the relative risk of different cryptocurrencies. Using this risk model, investors are better able to gauge the stability and volatility of our selected cryptocurrency assets. This knowledge helps investors protect themselves from unexpected losses.

Using the Sortino Ratio, we also present the average returns as well as the ratio itself, with a higher value meaning that it is overall a better investment. Using this, investors will be able to gauge which cryptocurrencies as assets are the safest to invest in given negative volatility and average returns as well as which ETF is best to invest the assets in to maximize profit.

There still exist many unexplored potential causes for price changes in cryptocurrencies.

One area we did not explore is the effect major events have on prices. For instance how do prices change after a large earthquake, terror attacks, national leadership changes, etc. Knowing how the prices react to large scale events would give an active portfolio manager a significant opportunity to save or make money. Additionally, we have not looked into comparing the statistics about the technical implementation of cryptocurrencies to price changes. Statistics such as total number of coins for trade, block size, and transaction rates could potentially give signals to investors of coming price changes. Lastly, the results of our study will not remain relevant for more than a few years because of the rapidly changing public understanding and trust in cryptocurrencies. It will be important for investors to redo our calculations with updated data frequently.

5 Conclusion

As cryptocurrency prices sky rocket, it is becoming clear that they have potential to earn investors impressive returns on their investments. However, cryptocurrencies do not come without significant risk. Cryptocurrencies are extremely volatile, especially compared to stocks and foreign indices. The volatility index we propose in this paper found the aggregate cryptocurrency risk to be 1,540% greater than the aggregate stock risk. Due to the levels of risk, investors would be wise to take in all the relevant knowledge possible before purchasing cryptocurrencies. There exists extensive knowledge about how to predict stock price changes and through our analyses we have shown that the same knowledge may be helpful for predicting price changes in cryptocurrencies. Our results show that the knowledge based around the technology sector of stock markets is the most relevant for predicting prices changes. Furthermore, our results show that cryptocurrencies are no longer good opportunities for portfolio diversification as was posited in [1].

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Appendix

On my honor, as a University of Colorado at Boulder student, I have neither given nor received unauthorized assistance on this work.

Contributions by Ethan Parks:

- Data collection for stock prices
- Data cleaning for initial pipeline
- Correlation computations between cryptocurrencies and corresponding chart creation

- Correlation computations between stocks and cryptocurrencies and corresponding chart creation
- Presentation slide creation
- Paper writing

Contributions by Jarrod Raine:

- Code for Sortino Ratio Calculations
- Contributed to Project slide finalization
- Paper writing/formatting/finalization

Contributions by Daniel Schwabacher:

- Risk analysis and modeling across cryptocurrencies, ETFs and foreign markets.
- Code for volatility calculations and plots
- Foreign index/market research
- Data collection for BTC
- Contributed to presentation slide creation
- Paper writing/formatting

Contributions by John Michael Scott

- Data collection for foreign indices, non-stock assets.
- Code for correlation calculation and visualization by year and between crypto and non-assets.
- Paper writing.