An Analysis on Cryptocurrencies

Christopher Streiffer

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Abstract

Over the past year, there has been a significant increase in the attention paid to cryptocurrencies. The total market capitalization of this emerging market has risen from $28 billion in April of 2017 to its current value of $430 billion, and achieved an astounding peak value of $830 billion in January of this year. What started with Bitcoin in 2009, has evolved into a multi-billion dollar industry where wild speculation and sentiment fuel high volatility and growth.

While there has been a significant increase in investor interest in this market, there is still a large amount of uncertainty associated with properly evaluating the performance and value of these assets. The Carhart four-factor model presents a methodology for determining the price of an asset based on its exposure to the market, size, value, and momentum. While this asset pricing tool can explain variations in the returns of traditional assets, no such model exists for analyzing cryptocurrency assets. While such a model would be useful, high variance and large magnitude price swings make cryptocurrencies difficult to model.

To this extent, this work presents an initial statistical analysis on the price volatility of cryptocurrencies, constructs an aggregate market index for capturing crypto market exposure, and conducts an analysis of individual asset exposure to variations of the index. Overall, this work shows that using traditional methodology for explaining variation in returns falls short when being applied to cryptocurrencies and presents a potential crypto-index factor worth further exploring in future work.

1 Introduction

In 2009 Satoshi Nakomoto released his now infamous white paper "Bitcoin: A Peer-to-Peer Electronic Cash System" [10]. The fundamentals of the paper detailed a secure, immutable peer-to-peer system for transferring virtual currency between pseudonymous users. The technology fueling this exchange provided two interconnected contributions to the field of computer science. The first was a consensus algorithm for solving the Byzantine Generals problem [8] at a large scale (>1000 nodes) known as *proof-of-work*. The second and most widely known contribution was providing the world with its favorite new buzzword – blockchain.

Since the inception of Bitcoin in 2009, the cryptocurrency market has experienced exponential growth. Today, there are over 1,500 different cryptocurrency tokens that can be bought and sold on exchanges and through Over-the-Counter (OTC) trades [7]. Bitcoin alone has over 20 different variations in circulation, with the most popular being Bitcoin Cash and Bitcoin Gold. During this period of growth, the total market capitalization increased from roughly $1 billion to the $430 billion behemoth that exists today.

This rapid increase in price, often compared to the tulip bubble [6], allowed for early investors to quickly tulipbubble a small fortune, and instilled a desire in others to achieve similar success. Today, cryptocurrencies are traded and held by investors ranging from hedge funds [11] to financial institutions [4] to everyday hobbyists who were able to successfully navigate Coinbase's Know Your Customer (KYC) registration process. Still, there is little public research available that provides statistical methodology for evaluating the performance, price, and returns of these assets. While multi-factor models [3, 9] provide a mechanism for computing the expected returns of traditional assets e.g. stocks, cryptocurrencies lack such a design. While this is still a young market, a multi-factor cryptocurrency model would be beneficial for performing asset pricing in the future and would open the door for more traditional investing practices.

To this extent, this work presents an initial statistical and CAPM analysis. The remainder of this work is structured as follows: Section 2 presents a description of the data used within this work. Section 3 presents an overview on the distribution of returns for different cryptocurrency asset classes and constructs an index model using the market capitalization of the top performing cryptocurrencies. Section 4 details the results of a traditional CAPM analysis on cryptocurrency assets, and presents an alternative CAPM analysis using the constructed cryptocurrency index. Section 5 presents a time-varying analysis beta analysis, showing how the exposure risk of an asset changes over time. The final section reflects on the findings of this work and presents future directions for this work.

2 Data

The analysis presented in this paper uses cryptocurrency market data collected from CoinMarketCap [1] and S&P 500 data collected from Ken French's data library [5]. The cryptocurrency data can be divided into two distinct datasets – small and large market cap asset classes. The large market cap asset class (LMC) consists of the largest 20 cryptocurrencies, while the small market cap asset class (SMC) consists of the next 80 largest cryptocurrencies. The data is collected across a daily rate during the time frame of April 28^{th} 2013 through February 28^{th}, 2018. Returns for the cryptocurrency data are computed as percent change between the open and close values for the given day.

3 An Overview of Cryptocurrency Markets

This sections provides a statistical overview on various cryptocurrency assets. The first sections presents a methodology for computing the aggregate cryptocurrency market index, or CCIX for short. The second section shows distribution statistics of the CCIX, LMC, and SMC.

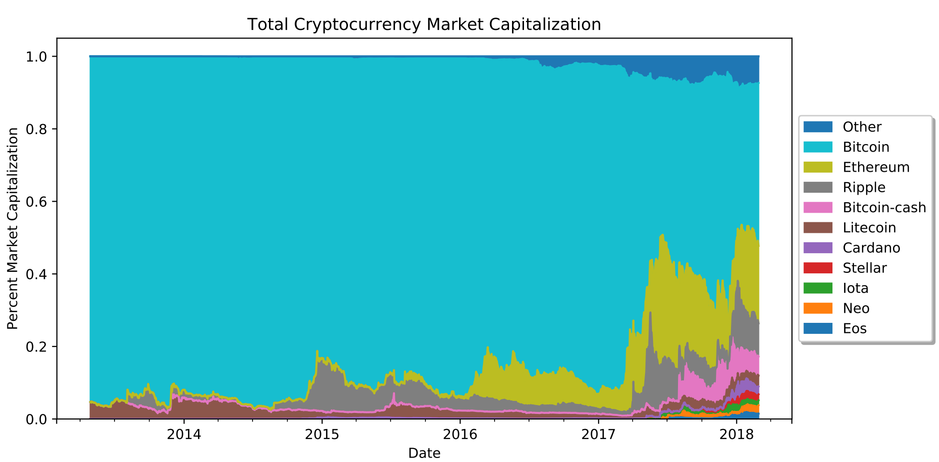

Figure 1: Weighted market capitalization of top 20 performing cryptocurrencies. Only the top 10 are displayed, the rest are grouped into Other.

3.1 Aggregate Crypto Index

The first step of this work was to construct an aggregate cryptocurrency market (CCIX). The CCIX uses a market-value weighted summation across the LMC asset class to derive its value. These assets are used because they have existed significantly longer than the SMC asset class and account for the majority of the market capitalization. According to the CAPM, this is an approximate of the optimal crypto portfolio. The weight for a given asset i within the portfolio at a given point in time t is computed using the following formula:

$$w_i, t = \frac{MC_i, t}{\sum\limits_{j \in LMC} MC_j, t} \tag{1}$$

Where MC_i is the market capitalization for asset i and LMC, again, is the large market cap asset class. Figure 1 shows the evolution of the index weights over time. As can be observed, between 2013 and 2017 Bitcoin dominated the market capitalization. From 2016-2017 other cryptocurrencies such as Ethereum, Litecoin, and Ripple started gaining popularity and taking away from Bitcoin's market dominance. Today, Bitcoin still holds the largest market capitalization, but the entire market capitalization is significantly diversified.

The value of the CCIX for a given day t is computed using a weighted summation across the different cryptocurrencies within the LMC asset class and is formulated as follows:

$$CCIX_t = \sum_{i \in LMC} w_{i,t} v_{i,t} \tag{2}$$

Where $w_{i,t}$ is derived using Equation 1 and $v_{i,t}$ is the closing value of cryptocurrency i on day t. The returns for the index can therefore be computed by taking the weighted percent change between the open and close values for day t. Figure 2 shows a plot of the total value of the CCIX and a bar chart displaying the returns for each day.

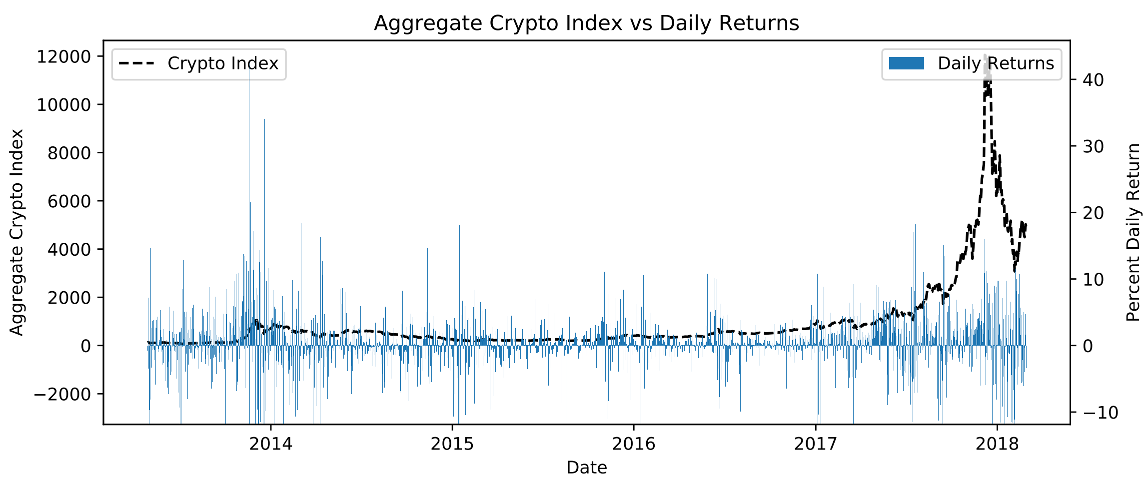

Figure 2: Performance of CCIX over time plotted against daily returns of the CCIX. 2017 marked the beginning of a bull run as the market capitilization of cryptocurrencies began its historic run.

3.2 Cryptocurrency Return Statistics

Once the index was constructed, the next step was to perform a statistical analysis on the returns for the different asset classes and the CCIX. Figure 3 displays a histogram of returns fitted to a normal distribution. The first distribution, CCIX, has a mean daily return of 0.35% with a standard deviation of 4.4%. The

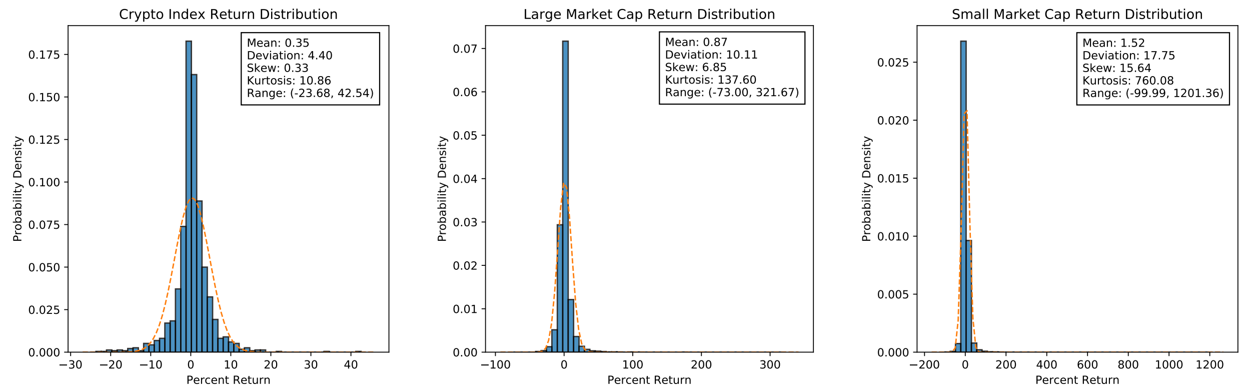

Figure 3: Statistical distributions for the CCIX (left), LMC asset class (center), and SMC asset class (right). The histogram is fitted with a normal distribution curve and the statistics for the distribution are shown.

skewnewss statistic shows that the distribution has a longer tail on the side of positive returns, while the kurtosis statistic shows that more of the mass is distributed towards the tails. While this distribution resembles a standard normal distribution, the fits for the LMC and SMC present very interesting results.

Starting with the LMC class, which has a mean and standard deviation of 0.87% and 10.11%, the range of returns falls between -73.00% and 321.67% for a single daily return. The skewness and kurtosis statistics encapsulate this behavior with values of 6.85 and 137.60. The SMC asset class even further exemplifies this anomalous behavior with skewness and kurtosis values of 15.64 and 760.09. In fact, the range of of the SMC asset class falls between -99.99% and 1201.36%, indicating that an investor could either be completely wiped out or retire early depending on the mood of the day.

The results of this analysis shows that investing in these assets means that anomalies, or values found at the tails, have a higher density than what would be found in a standard normal distribution. Out of the three analyses, the CCIX, LMC, and SMC produced sharpe ratios of 0.080, 0.086, and 0.86. However, the abnormal shape of the LMC and SMC asset class analyses begs the question as to whether these ratios actually have any merit.

	Value	BTC	ETH	XRP	BCH	EOS	LTC	ADA	XLM	MIOTA	NEO
CCIX	$E[r_i] - r_f$	0.33	0.90	0.63	0.99	1.70	0.44	3.05	0.77	0.99	2.12
	α	-0.01	0.44	0.32	0.22	0.86	0.04	1.97	0.48	0.29	1.46
	p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	β	0.99	0.96	0.80	1.00	1.21	1.15	1.30	0.92	1.16	0.96
	p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
S&P 500 Index	$E[r_i] - r_f$	0.37	1.11	0.81	1.64	1.85	0.45	3.27	0.81	1.22	2.41
	α	0.37	1.09	0.79	1.69	1.71	0.45	2.93	0.78	1.07	2.57
	p-value	0.01	0.00	0.00	0.16	0.07	0.07	0.15	0.01	0.26	0.01
	β	0.03	0.51	0.42	-0.64	1.73	-0.03	3.87	0.62	2.02	-2.25
	p-value	0.87	0.18	0.20	0.70	0.20	0.93	0.13	0.11	0.15	0.14

Table 1: CAPM Analysis: Time-series regression using CCIX and S&P 500 Index to compute excess cryptocurrency asset returns.

4 CAPM and Cryptocurrencies

This sections seeks to answer the question "can the variance in returns for cryptocurrencies be explained by exogenous factors?" The Capital Asset Pricing Model (CAPM) provides a mechanism for relating the excess return of an asset to systematic, or market, risk [2]. In a traditional CAPM analysis for a given asset, the systematic risk is computed as the excess return on the market, and the asset's exposure to risk can be computed by solving the following time-series regression:

$$r_{i,t} = \alpha + \beta(r_{m,t} - r_{f,t}) + \epsilon_i \tag{3}$$

Where $r_{i,t}$ is the return of the asset, $r_{m,i}$ is the return on the market, $r_{f,i}$ is the risk free rate, and ϵ_i is random error. Once solved, the β coefficient represents the asset's exposure to the market's risk, while α represents the abnormal return of the asset itself, and can be thought of as a bonus.

To assess cryptocurrencies exposure to different types of risk, this analysis performs a CAPM evaluation using the S&P 500 Index and the CCIX. The first stage of the analysis is to perform a time-series regression for each asset to determine its α and β values. Because the S&P 500 Index does not trade on weekends or federal holidays, these values are ignored within this analysis. Using Equation 3, the results of the regression using both indexes can be found in Table 1.

The results of the analysis show that the betas computed using the CCIX have strong statistical significance ($p < 0.001$). Further, the majority of the beta values computed for the cryptocurrencies fluctuate around 1. This is fairly consistent with the notion that the cryptocurrency market is highly correlated.

While the beta values economically and statistically make sense, the CCIX regression also produced statistically significant alpha values for the majority of the assets. This shows that there are additional factors that the CCIX alone cannot fully explain.

The results of the S&P analysis show a high variation in the betas as computed by the regression. Further, the majority of these computed betas have high p-values (> 0.05). This indicates that the results are not statistically significant.

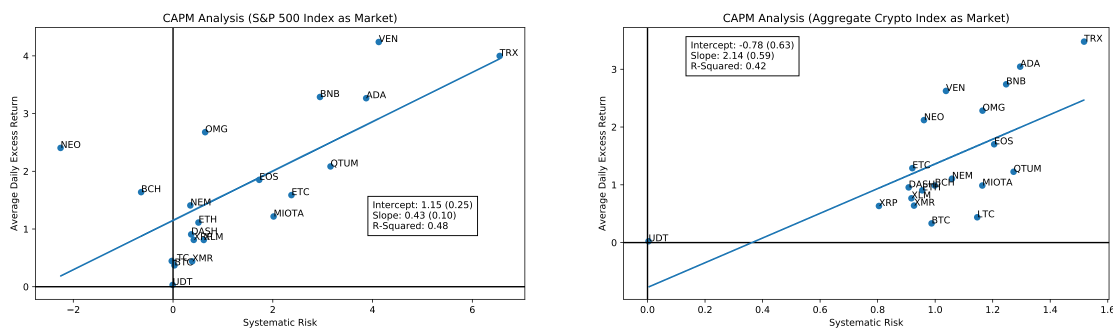

Figure 4: Cross-sectional regression using betas computed using the S&P 500 Index (left) and CCIX (right). The regression line is displayed for each dataset, and the resulting statistics can be observed.

The second stage of the analysis performs a cross-sectional regression using the computed beta values from the first stage. The regression can be computed using the formula:

$$E[r_i] - r_f = \alpha + \beta(\beta_i) \tag{4}$$

Where i represents each of the assets computed using the model and $E[r_i] - r_f$ represents the expected daily excess return. The results of this regression can be observed in Figure 4.

Besides Tether (UDT) which is designed to be a stable coin, the regression line for the CCIX analysis does a good job of estimating the values for beta, and can explain roughly 42% of data. The regression line for the S&P 500 Index also has a high R-squared value of 48%; however, due to the results from the time-series regression, these results should not be viewed as statistically significant.

Overall, the conclusion that can be drawn from this analysis is that the traditional CAPM analysis fails for cryptocurrencies and that the CCIX presents a factor which can partially explain variations in cryptocurrency returns.

5 Time-varying Beta Analysis

This section looks at a time-varying beta analysis between the CCIX and the following cryptocurrencies: Bitcoin, Ethereum, Ripple, and Dash. These cryptocurrencies were selected due to their large market capitilazation and because they have existed for a comparatively large duration of time.

The analysis is performed by computing the beta coefficients using the aforementioned time-series regression across a 10-day sliding time window. For instance, the beta coefficient for time step t is computed by solving the linear regression across the time-window $[x_{t-5}, x_{t+5}]$. This sliding time-window regression is repeated across the entire dataset for each cryptocurrency, and the results of the analysis are plotted and observable in Figure 5.

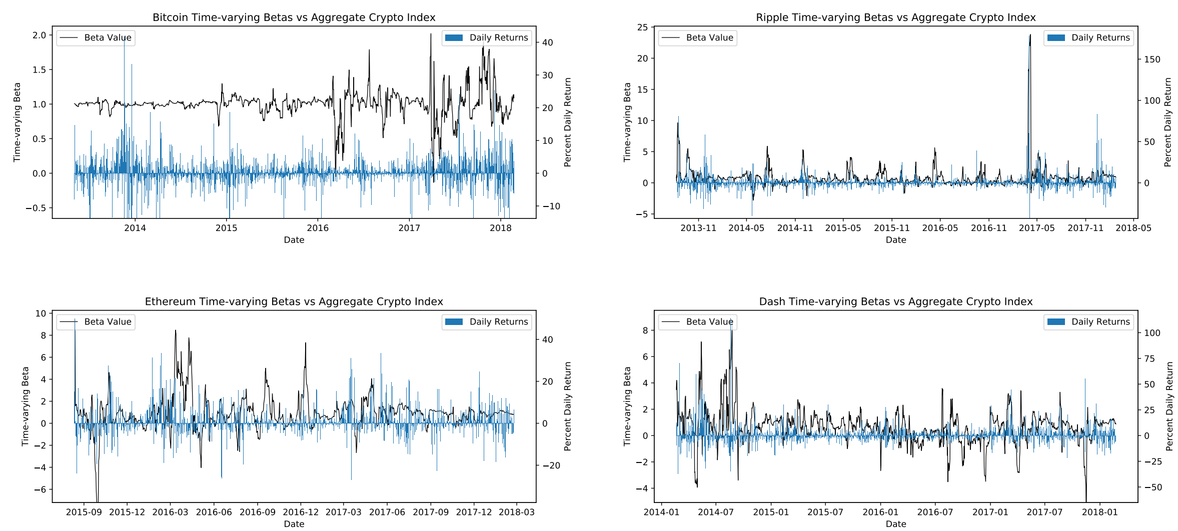

Figure 5: Time-varying beta analysis for Bitcoin (top left), Ethereum (bottom left), Ripple (top right), and Dash (bottom right). The betas are plotted against the high variance of the market to highlight volatility trends.

The most immediate observation is that excluding Bitcoin, the other cryptocurrencies display trends which show high variation in changes of beta. Isolating large magnitude changes made by the CCIX shows that the betas for these assets are significantly sensitive to this volatility. Sepcifically, Ethereum and Dash both display positive and negative betas across their entire time frame, seemingly jumping back and forth across this boundary. Ripple displays an interesting trend in that it typically maintains a low beta, but can have momentary spikes during times of high volatility.

Due to the dominance of Bitcoin on the market, it is not unexpected that its beta remains fairly consistent with a mean of 1. The results show that from 2013 to 2016, Bitcoin primarily decided the market, and thus had constant 1:1 exposure with the CCIX. After 2016, the variance of Bitcoin's beta increased drastically, while it's mean remained around 1. This change can be accounted for by the changing market capitalization due to the rise of competing cryptocurrencies. As can be observed, the beta for Ethereum reduces in volatility during this time, possibly indiciating a decrease in market dominance by Bitcoin.

Overall, this analysis shows that the beta coefficients are highly sensitive to variations within the CCIX. This high volatility shows the difficulty of producing a consistent model for pricing these assets.

6 Conclusion

The market for cryptocurrency is still in its infancy, and thus, so is the analysis that exists around it. While traditional multi-factor models work well for analyzing stocks, cryptocurrencies seem to live on their own island. As can be observed by the CAPM analysis, they have a large amount of insulation from S&P market risk. Because they do not trade on typical fundamentals, it would be interesting to construct a new multi-factor model in futue work. Using an index such as the proposed CCIX offers a good starting point for explaining some of the variation in returns, but clearly other factors exist which can further explain these variations. While this might not be useful now due to high variance and volatility, as the market matures, a multi-factor model will be useful for correctly analyzing and pricing these endearing, ludicrous assets.

References

[1] 0x0074709077B8AE5a245E4ED161C971Dc4c3C8E2B (2018), "CoinMarketCap," .

[2] Brennan, M. J. (1989), "Capital asset pricing model," in *Finance*, pp. 91–102, Springer.

[3] Fama, E. F. and French, K. R. (1996), "Multifactor explanations of asset pricing anomalies," *The journal of finance*, 51, 55–84.

[4] Floyd, D. (2018), "1 in 5 Financial Institutions Exploring Crypto Trading, Survey Finds," .

[5] French, K. (2018), "Current Research Returns," .

[6] Gewirtz, D. (2018), "Cryptocurrency comes with one colossal caveat: Remember the tulips," .

[7] Irrera, A. and Kelly, J. (2018), "OTC crypto market flourishes, powered by Skype," .

[8] Lamport, L., Shostak, R., and Pease, M. (1982), "The Byzantine generals problem," *ACM Transactions on Programming Languages and Systems (TOPLAS)*, 4, 382–401.

[9] LHer, J.-F., Masmoudi, T., and Suret, J.-M. (2004), "Evidence to support the four-factor pricing model from the Canadian stock market," *Journal of International Financial Markets, Institutions and Money*, 14, 313–328.

[10] Nakamoto, S. (2008), "Bitcoin: A peer-to-peer electronic cash system," .

[11] Parmar, H. and Waite, S. (2018), "Crypto, Taxes & Volatility: A Hedge Fund Watch List For 2018," .