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Examination of the Divergence in Alternate Trading Pairs

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ABSTRACT

When it comes to cryptocurrency, there are many varying opinions on every aspect of this brand-new asset. Within the context of this research, the disparities in price movements are the aspect in question, and this is the part of cryptocurrency that all stakeholders know the least about. There are some that say it is a hedge to different markets, and there are others that claim that they can use chartist methodology to find technical patterns. Whether these methods are true or false, they have something in common: they are based on standard market fluctuations that have been seen in equity and debt markets. Clearly, from what the world has seen, crypto markets are anything but traditional, but that is not to say that somewhere down the line this market will not converge to some fundamental standard. To explore the price movements of cryptocurrencies, I decided to analyze functions that are related only to the cryptocurrency market. More specifically, I chose to analyze convergence and divergence of correlation to Bitcoin, high volume trading pairs, and the market as a complete bucket to see if there are any potential opportunities that can be exploited for profit given current technological capabilities.

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Chapter 1 Overview

Background

Over the history of markets, there has been an emphasis and extreme amount of effort put towards deriving forward-looking trends based on historical data. There are many sides to the argument of whether or not this is a viable solution. Many argue that markets are fully efficient, and there is no ability to “conquer” markets by using backward looking data. This is the short form of the Efficient Market Hypothesis. However, there are many that claim that markets follow predictable trends over the short and long run, which would allow for some sort of alpha to be generated through programmatic trading.

Over the past half century, there have been major advances in computational technologies as well as established networks which bridge computational possibilities directly to data sources. A major example of this was the Pioneer Dr. Jim Simons, who created some of the first connections between markets and machines. Teitalbaum highlighted Simon’s first attempts by hiring data analysts to enter historic pricing data into computers so that they could be manipulated and searched for pricing patterns that could potentially be traded for profit (Teitalbaum, 2008). Since the beginning of the machine and market marriage, there is one fact that has exacerbated the difficulty of attempting to derive value from this relationship. Many of the attempts have been focused solely on equity and foreign exchange markets. Both of these markets are quick, advanced, and have been around far longer than systematic computation itself. Therefore, there has been no ability for technology and these markets to grow together; rather, it has been systems attempting to catch up to the market.

With cryptocurrencies, the exact opposite is true. Systems came far before cryptocurrency, so therefore the use of systems can be developed alongside the market as it grows and matures. The cryptocurrency market draws many parallels to primitive equity, debt, and other asset-based markets. For example, there are similar measures of volatility like beta and various others. The market is also similarly structured with common metrics like share prices and market capitalizations. However, the ownership structure is clearly very different given that there is no partial ownership of any tangible item in cryptocurrency. The major trend that is examined in this work is the dominance of a given asset to another. In primitive and modern equity markets, certain assets tend to trade in line with one another. For example, smaller public banks may trade in line with the KBWB Banking Index (NASDAQ: KBWB), meaning that if the KBWB trades down, then the bank stock may fall regardless of fundamental causes.

In cryptocurrency, the dominance is derived from Bitcoin given that it makes up over 45.00% of the market currently according to CoinMarketCap.com (CoinMarketCap.com, 2023). This dominance is exerted over other cryptocurrencies, which are also known as alternative pairs. This dominance is also more potent as compared to equity markets given that there is arguably no fundamental basis on which these assets trade upon. For equity markets, there is a company that backs and influences the share price which somewhat insulates the shares from major price swings solely based on other assets. However, for cryptocurrency there are many factors that tie all of the alt pairs to Bitcoin.

The first major influence that Bitcoin has over the other cryptocurrencies is the fact that it has long been the "liquid" asset in which these alt pairs are traded. More specifically, many primitive and modern exchanges have allowed users to only trade using Bitcoin. For example, the symbols will be shown as "ETH/BTC", meaning that Ethereum can be purchased and sold using and in exchange for Bitcoin. No actual cash is being transferred in these instances due to strict money transmission laws. This provides an extreme barrier to entry in terms of alleviating

Bitcoin dominance over alt pairs. The need to exchange can be rationalized by comparing it to debt and foreign exchange markets. If another country wants to buy United States debt, it must do so in dollars. Therefore, the demand for the dollar goes up and increases its value relative to other currencies. The same can be said for Bitcoin, if someone wants to buy Ethereum or any other cryptocurrency, they must do so in Bitcoin. This increases the demand for Bitcoin and raises its price. Given that this is extremely common amongst exchanges and trading pairs, this increases daily volumes of Bitcoin by an extreme amount and solidifies Bitcoin's dominance.

Not only does Bitcoin's liquidity hold influence its own price, but it also influences the price of other cryptocurrencies as well. Given that the cryptocurrency market is highly speculative, it is true that people will buy and sell alt pairs based on price movements in Bitcoin. However, it can be looked at from a "fundamental" perspective as well. When investing in United States equity markets, it almost always must be done so through the dollar. However, if the dollar starts to devalue relative to other currencies, that has a major fundamental impact on the value of United States equities which will lead to relative trade downs if all else is equal. The same can be said for cryptocurrencies in terms of Bitcoin's value. There is also a major factor in the panic of trying to get liquidity in these markets. Given that many users must convert pairs to Bitcoin in order to get cash, devaluation of Bitcoin can lead to panic in the market which negatively impacts prices. This can lead to major horizontal declines across the cryptocurrency market.

The major trend that is analyzed from this dominance is the correlation convergence and divergence from the dominant asset. More specifically, if an alternate pair has a general correlation with Bitcoin and it diverges from that, the goal is to determine whether or not it will converge back to that normal value. If that can be determined, there is the ability to make an educated trade for profit based on logic that will be explained later in the piece. In the modern day, there is a somewhat easy ability to analyze price movements programmatically using various libraries and advanced programming interfaces (APIs). Therefore, a large amount of data can be analyzed across pairs to determine intraday and long-term correlations, and whether or not they are maintaining a normal magnitude compared to their historical mean.

Chapter 2 Literature Review

Traditional Cryptocurrency Drivers

A general market metric that has become standard in most asset classes is the value of beta. That is the covariance of returns of one asset to the designated benchmark over the variance of the benchmark. This helps investors gauge how risky an asset is compared to a benchmark, leading to a more informed decision-making process. In theory, the higher the beta of an asset, the higher the expected return it should generate over the long run, but the higher risk it will take on as well. The beta metric is generally used over the long run and has a normal period of greater than a year. Of course, this metric cannot truly be used on crypto markets and pairs given that many of them have had major shifts in how they trade and the overall sample size. Additionally, there is no true market to compare them to given that the cryptocurrency markets are active twenty-four hours a day, and the only similar iterative market is foreign exchange which lacks volatility and is far too fundamentally bound. Furthermore, Chuck Carnevale denounced the notion that beta is the greatest measure of risk and pushed investors to look elsewhere (Chuck Carnevale, 2015). I agree with this notion which is why I have chosen to look at correlation as the measure to search for a buying opportunity. Correlation also fits the crypto market a lot better given that there is such a large amount of pricing data in the short run due to quick trading and the market being constantly active. Correlation also accounts for the movement of the benchmark which will help to refine skew from more standard metrics like variation and standard deviation of prices, which cannot be truly standardized across pairs.

Carnevale also stated that academia has a very narrow sense of what risk truly means within markets (Carnevale, 2015). This is accompanied by the statement “importantly, if you really carefully consider the above definitions of beta, it should be clear that they are full of theory, but not necessarily full of fact" (Carnevale, 2015, p. 3). Since beta measures are very long duration measures, it can be true that no beta value is truly accurate since it requires a long interval to produce. With markets moving so fast there is the need for a quicker measure, which is correlation. Pioneers have tried to use traditional models on crypto assets which have had a fair share of disparity. Botte and Nigro tried to implement their Two Sigma model, which is a model based on heavy amounts of well-established assets, to price Bitcoin (Botte &Nigro, 2021). This ultimately failed and resulted in 91% of Bitcoin's risk going unaccounted during January of 2015. This is in comparison to Apple (NASDAQ: AAPL) which had 51% of its residual risk unexplained during the same period.

Cryptocurrency General Market Movements

As previously mentioned, it has become clear that cryptocurrency is highly volatile. Price can move hundreds of percentages in a single twenty-four hour period and then crash the very next day. One of the major goals of this research is to try and map how exactly the market moves and what makes it tick. In a staple article, CNBC asserted that Bitcoin dominance plays a major role in how the overall market moves (CNBC, 2022). This article was an inciting force that led to this research, but Bitcoin dominance is not the entire reason for how crypto markets move. Bitcoin dominance is essentially Bitcoin's market capitalization divided by the entire cryptocurrency market capitalization. Simply, it measures how much of the overall market is held up in Bitcoin compared to alternate coins. CNBC further explains that this dominance has played a major role over the history of crypto, but it is declining over time (CNBC, 2022). As more alternate coins join the profit frenzy, it seems that they are overtaking the top crypto. Ciaian gave reason for this change with the introduction of fiat exchanges (Ciaian, 2017). When cryptocurrency was initially released, the only way to buy it was with other cryptocurrencies or very shady transfers that were usually facilitated over person-to-person (P2P) networks. If an investor wanted to buy an altcoin like Litecoin, then they would have to first purchase Bitcoin and then exchange for Litecoin. This occurrence can be thought of similarly to monetary policy responses by foreign nations. If the United States increases from the zero-bound interest rate, then foreign investment will flow in and be converted to dollars. This will then appreciate the U.S. dollar as it relates to that currency. In the cryptocurrency example, the dollar was exchanged for Bitcoin, and the Bitcoin was either held or exchanged for another altcoin. Therefore, the price of Bitcoin appreciated compared to the dollar and the altcoin, deriving the dominance that has been discussed.

Suberg explained that the fiat exchange that can purchase altcoins has almost single handedly destroyed Bitcoin dominance (Suberg, 2022). A fiat exchange allows users to use credit cards and bank transfers to buy an array of cryptocurrencies for cash. This leads to price appreciation across the market rather than just Bitcoin. This would be like the U.S. Federal Reserve expanding from a single T-Bill to the catalogue that is present today. This also gives a more fundamental backing to these cryptocurrencies given that the blockchains that they are based on vary in terms of settlement time. If a person wants to get their money into a certain pair, it may be advantageous to use the fastest base pair available to lock a price in faster. This has been seen with Ethereum given that its settlement time is so high. This has been implemented in Non-Fungible-Tokens (NFTs) where the main exchange is almost always with Ethereum due to its speed. This has created extreme adversity for Bitcoin dominance.

Interdependence & Iteration Intervals

Ciaian highlighted the fact that Bitcoin and altcoins are interdependent even though the dominance has gone down (Ciaian, 2017). Being the largest cryptocurrency and with many altcoins still trading only under BTC pairs, there is still a heavy reliance from a liquidity perspective. It is also the cryptocurrency that seems to feel safer given that it has been around for such a long time and has seen the highest overall return since inception. The conclusion that was found by Ciaian was that altcoins are interdependent over the short-run but cannot be statistically shown to be interdependent over the long-run (Ciaian, 2017). For this reason, any sort of production implementation of these findings must be able to exploit price movements quickly so as not to miss out on major buying opportunities.

Given the findings of Ciaian, it has become apparent that short intervals will work best for research and implementation of an eventual system. However, a major constraint of this research is to stay within the realm of current or feasible capability. High frequency trading firms have a far higher capability to perform trades, but that does not correlate with cryptocurrency. High frequency trading firms pay millions to move inches closer to exchanges. Cryptocurrency exchanges are hosted on distributed servers which decreases the effectiveness of this strategy. For that reason, a general API that connects to a cryptocurrency exchange should be fast enough to make some sort of solution.

Similar Attempts

Vidal found that 58% of altcoins had correlations to Bitcoin greater than 60% following a major “bull run” (Vidal, 2020). Vidal also found that many of the top altcoins correlate higher than 60%, making the indication that the market may be somewhat top-heavy (Vidal, 2020). This is also seen at the top of sectors within equity markets. In each day, many large similar companies will trade in a similar direction which indicates that there is high short-term price correlation amongst these symbols. Vidal found that correlations change over time, but they tend to really change to their original values during extreme price movements of Bitcoin or coins at the top of the market (Vidal, 2020). Therefore, this could lead to the fact that there is a possibility that this can be programmatically exploited.

Overall, it seems that price influences within the cryptocurrency market have evolved over time. However, the same can be said for equity markets as well. Over time equity prices have been pulled from their fundamental foundations and been transformed into completely different entities. One could say that a share of stock represents ownership in a company, but that would be like saying a dollar is still represented by an equal amount of gold. Equities have become more like derivates in that their price levels have changed backing so much that they almost mirror cryptocurrency. For the sake of conducting fair research, it is the goal to not draw completely from equity pricing methods, but it would be dishonest to say that there are no similarities.

Chapter 3
Assumptions & Research Foundations

In order for this thesis to be accurately assessed, it is important to understand the assumptions that it is based on. As with any financial modeling, there needs to be assumptions to account for the overall complexity of beating the market. All assumptions that are made from a technology perspective are all feasible in terms of current technology available to retail investors. All analysis was done in Google Collaboratory, an open source and free python notebook that is hosted online. The notebook gives users the ability not only to share data and code with other users, but it also has a suite of tools that make programming far more organized. The major tool that has been leveraged for this thesis is the use of a hardware accelerator via a virtual GPU. Google allocates this for free and it allows the user to process higher throughputs of data which was extremely helpful for this analysis. It can be assumed that this could be duplicated by a retail investor and that institutional investors would have the ability to perform this acceleration at a higher scale.

One of the major assumptions that this thesis is based on is the fact that all data that is analyzed is periodic rather than constant. Therefore, all statistics that were computed were sample rather than population given that every pricing data point is not and could not be included in the analysis. This is common for most pricing algorithms that are created, with many of them using daily pricing rather than instantaneous price signals that are hard to obtain, potentially inaccurate, and require extreme computer and networking power to constantly receive and process. It can be assumed that this would likely not be possible for the average retail investor currently.

Another assumption that this research makes is that price correlation can be compared to itself historically to derive future price direction. The research does not aim to predict exact or approximate price estimates; rather, it aims to predict direction. Many researchers claim that there is no ability to look at historical prices to derive price direction, but that is an assumption and hypothesis that is fully omitted from this research. This research refutes even the weak form of the Efficient Market Hypothesis which states that current prices reflect all past pricing information. In this form, there would be no ability to predict price movements with any fundamental or technical analysis.

This research also refutes the Random Walk Theory, which states that asset price movements are random and that markets are fully efficient (Fama, 1965). This theory also states that there is no ability to time that market and that investing in indexes is the most logical way to invest (Fama, 1965). Although price movements, especially in cryptocurrency, may be random in the short run, over the long run this paper assumes that prices are somewhat predictable from a directional perspective and that this timing may be achieved by measuring and comparing historical correlation. However, this is assumed to be somewhat unique to the cryptocurrency market as opposed to equity and debt markets. The reason for this is that there is no single asset that is far larger and more dominant than Bitcoin compared to alt coins. This dominance could be seen in federal debt markets with the domination of U.S. rates over retail and commercial lending. However, these rates are manually set by the Federal Reserve via open market operations, whereas Bitcoin is fully a free and open market asset.

The analysis of pairs is done so without any sort of bias towards larger market capitalization coins. The pool of pairs that was selected for analysis was based on the top list of traded cryptocurrencies and they must have available pricing data for the past five years in order for the analysis to be equal and parallel across pairs. Liquidity pairs were specifically omitted given that they try to mirror the value of the dollar statically. These pairs include USDC, USDT, and various other exchange specific liquidity tokens. The system solely evaluates based upon price movements, and does not take into account any news, fundamental, technical, or other indicators for its trade logic. Although this could be implemented in the future with the emergence of natural language processing, the goal of this thesis was solely to determine the movement of correlation.

Finally, the research assumes that all pricing data is accurate as of the end of day for each given period. Although cryptocurrencies are traded all day and 365 days a year, the period is at the end of UTC time, which is the time zone that computers are able to understand by default. This also helps to keep the timing constant for any further research. Additionally, this research also assumes that all prices are reflective of peer to peer (P2P) dealings. It would be extremely difficult to gauge these transactions, as many of them involve exchanges of goods for cryptocurrencies or other services which are not widely tracked or reported. The correlation analysis assumes that all pairs have been constantly traded over the five-year period. Although this may not fully be true due to exchange breakdowns and various other events, it can be assumed that there is enough data to make up for these potential minor holes. Therefore, the data is equal across all alt pairs and Bitcoin over the analyzed period.

Parallels to Established Markets

Although cryptocurrencies are inherently different from any other market, the general functioning of all markets can be drawn together in many ways. For one, the general structure of the market is the same as that of equities. There are buy and sell orders that meet in order to create trades, and there are many similar metrics that are tracked like overall market size.

Additionally, there are trading pairs that are exchanged for different currencies such as BTC/ETH and BTC/USD. However, relating to this specific research, dominance of singular assets likely occurred over the more primitive parts of equity markets. Specifically within the New York Stock Exchange and undocumented P2P trading that occurred around the founding of the country, there was likely major market movers that dictated the overall market.

According to Patrick Randall, the East India Trading Company was highly overvalued in 1769, when there was a lack of capital in the general market, many shareholders sold their shares in the Company (Randall, 2016). Since the East India Trading Company was arguably the largest documented company at the time, this led to a major crash of shares across tradeable companies. This is an example of a very primitive form of dominance. Although there is no actual data on major crashes that were heavily impacted by the demise of one singular company, qualitative dominance can be seen in the present day. For example, Evergrande, a Chinese real estate conglomerate, announced in 2021 that it would default on a majority of its debt. This led to a major trade-down across Chinese related real estate companies and overall lenders. Although this is a more fundamental trade-down with a direct cause and effect, this shows some sort of dominance relating to the share price. Obviously, cryptocurrencies do not really have fundamental ties to one another, but the previously mentioned liquidity practices are somewhat similar.

Market Friction

Market friction is a phenomenon that occurs across all markets. Friction occurs when placing trades and involves the time it takes for a trade to be executed. This friction varies across markets and is commonly a sign of how liquid a market is. Market liquidity, or the ability to convert assets into cash or cash equivalents represents a common issue for algorithmic and traditional trading. Equity markets are considered to be highly liquid on the public side, and they are rather illiquid on the private side. Cryptocurrency markets have evolved over time to become more liquid given that many exchanges will convert most pairs to cash and deposit directly to bank accounts. However, there are still exchanges that only export Bitcoin which makes them far less liquid. In this research, general liquidity is assumed and that cash from a recent sell order will become immediately available to be used in a buy order.

General Signal Logic

The overall goal of the system is not only to identify the convergence and divergence of alt coin price movements, but it is also to capitalize on these identifications for potential real world trading applications. The general logic of the theoretical system would follow a set of dependent binary decisions that would be facilitated through python and that would be subject to real world limitations that are highlighted in the next section. However, there should be base line assumptions with the trades of the proposed system that may supersede the capabilities of the average retail investor, but that could be achieved by institutional and larger scale investors. This involves quick connection to markets, liquidity, and decreased market friction relating to trade execution times and overall placement of orders. Under the assumption that investors are rational, the system would not apply leverage given the volatility and primitive nature of the cryptocurrency market. Moreover, leverage in the cryptocurrency markets is historically inferior to that of equity and debt trading leverage. Therefore, it is not assumed to be consistent or logical enough to be implemented.

The trading logic of the system follows a specific set of rules that it will execute at all times with no human interaction needed. While analyzing pairs, the system will determine if there is divergence from the normal correlation of the trading pair to Bitcoin. From there, it will determine what percentage of the time the pair returns to the normal correlation or stronger. After determining which divergent pair is the farthest from the normal correlation and with the highest level of certainty for it to recouple, it does a secondary evaluation. That evaluation is as follows: if the price of Bitcoin is rising and the price of the pair is declining, then the system would assume that it is a buy signal. The reason for this is assuming that the pair will converge back to the normal correlation, it would have to rise in price to reform the relationship between Bitcoin and itself. Therefore, the assumption is that the best course of action would be to buy with the system's given amount of liquidity. The same can be said for the opposite, if the pair is trading up and is divergent, it would be best to sell the asset or buy its inverse if that opportunity is available.

Given that the system does not use any sort of margin instruments, it is assumed that there will be no short selling of assets. This is also primitive and rather unproven in cryptocurrency markets, but that could be changed in the future. It is fair to assume that the system will benefit from developments in exchange technologies and as further trust is placed on these intermediaries. However, it would be illogical to assume that the average rational investor would apply leverage in cryptocurrencies. The pricing of the alt pair would be at its last traded value which assumes that it is close enough for simulation purposes to the actual price of the cheapest sell order present in the market. This takes a major network load off of the system from having to search all exchanges and pairs for best pricing in a simulated environment, which would make it overtly slow. However, as previously mentioned, this would be something that could be easily achieved by larger investors with greater resources.

Free-Tier Limitations

As previously mentioned, this research could be conducted on many different scales. In the spirit of translatability, it makes most sense to use free tools that are available so that others could perform similar research as well. Even though tools like Google-Colab and Excel are free, they are powerful and industry grade. There is the ability to increase to premium plans on both with additional add-ins that would improve processing and computing power. The major limiting tool is Google-Colab which does a majority of the analysis and data scraping. Google generously allows users to access 12gb of ram and up to twelve hours of runtime. Therefore, complete analysis cannot fully be completed on a constant basis, but it more than fits the scope of this research. The Google-Colab Pro subscription would allow for complete analysis and higher processing power but will still not fit institutional capabilities that would be achieved from an extremely expensive Google Cloud server setup.

Hardware Constraints

The major constraints on the initial research side were computing power, ability to thread, and storage. As for computing power, the previously mentioned random access memory (RAM) of 12gb and the given central processing unit (CPU) is more powerful in Google-Colab than normal laptops, but it falls very short of virtual systems that can be used by institutional investors. Threading, which is a rather complex computing process, is the ability to run multiple different codes at once. For this research, Google-Colab was able to handle three processes at once, allowing the system to analyze three different pairs all at once. This is considerably faster than a normal laptop but falls short of institutional systems as well. Finally, the system was designed to use instance memory rather than saving every data point to system hard memory. Therefore, memory was only constrained by the number of pairs that could be analyzed and timeline of data. For this reason, it was best to conduct the research on a daily price basis to avoid running out of storage with intraday prices.

The trading side is where institutional investors would have a major advantage. Many high frequency trading firms have the ability to physically relocate to areas closer to exchanges which decrease latency. However, many others can rent servers that are located close to exchanges as well to decrease latency. Although the difference in timing would be small, timing signals would be heavily impacted, leading to quicker trades. The quicker the trades were able to be placed, the faster the theoretical alpha could be realized.

Chapter 4 Analysis Results

Identification Results

Data Composoition	Correlations	Data Points
Per Pair	1460.00	532900.00
Total	8760.00	3197400.00

Table 1. Data Composition

The system was able to analyze six different cryptocurrency pairs. These pairs were: Litecoin, XRP, Ethereum, Binance, ADA, and Doge. In total, there were 8,760 total correlations calculated with 365 days of data going into each correlation calculation. Therefore, over three million data points were able to be successfully downloaded and analyzed within thirty seconds of total runtime. This was able to be accomplished fully given the software and hardware constraints that were previously highlighted and would be fully replicable by any retail investor given current technological capabilities.

Symbol	LTC-USD	XRP-USD	ETH-USD	BNB-USD	ADA-USD	DOGE-USD
Average	0.877577769	0.731475591	0.795950153	0.718550268	0.720264536	0.507412509
Count Yes	591	631	468	656	556	550
Count No	3	0	0	2	17	0
Reversion%	99.49%	100.00%	100.00%	99.70%	97.03%	100.00%
Total Diversions	594	631	468	658	573	550

Table 2. Pair Breakdown

The figure above shows the breakdown of the average correlation over the five-year period. Additionally, it displays the number of times that a pair successfully reconverged to its average correlation or better as well as the number of times that it was not able to reconverge. The reversion percentage shows the percentage of the time that the pair was able to reconverge as well as the total number of diversions over the five-year period. In summary, the data was mostly parallel across pairs with minor disparities likely due to how established each pair is.

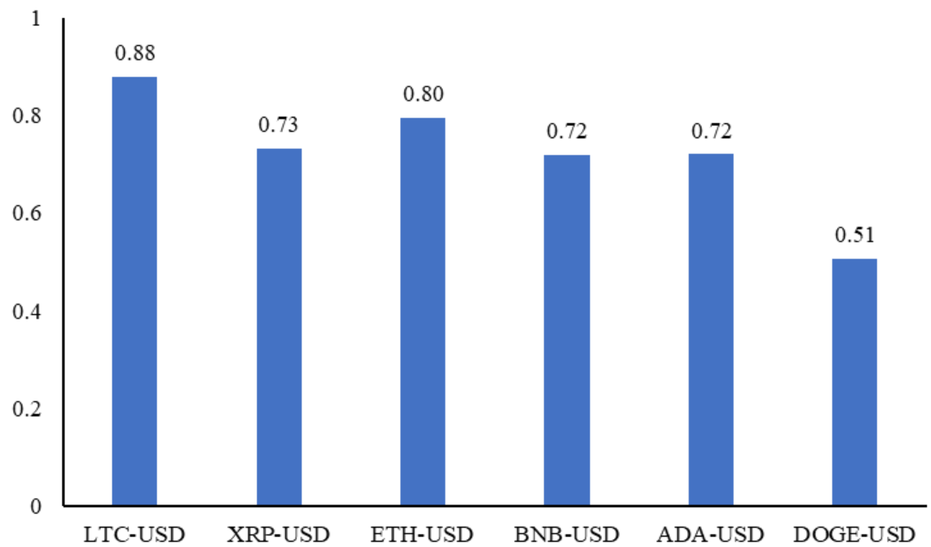
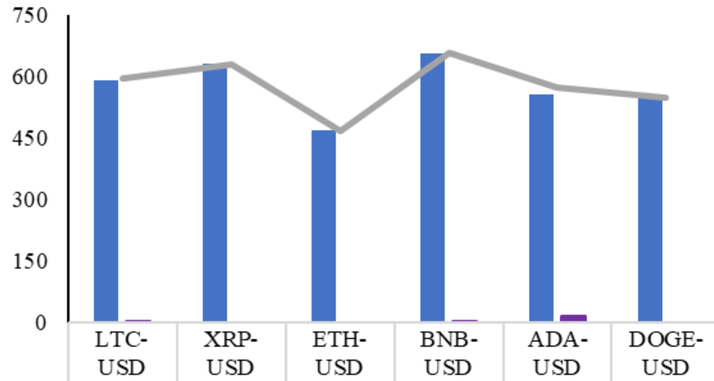


Figure 1. Pair Breakdown

As shown above, there were varying correlations between pairs, but all were strong positively correlated to price movement of Bitcoin over the long run. The more established coins like Litecoin and XRP had a higher correlation as compared to newer and less established coins like Dogecoin. This was different than the initial hypothesis that lesser established coins would blindly follow the price movements of Bitcoin given liquidity issues and less direct exchanges for USD. In summary, the average correlation over the analysis period was .601, representing a very high positive correlation. This measure was brought down mostly by Doge-USD, which is a highly speculative pair that has had a lot of volatility in the ladder two years of the analysis period. Overall, it can be concluded that price movements of these pairs are highly correlated to the price movements of Bitcoin over the long run.



	LTC-USD	XRP-USD	ETH-USD	BNB-USD	ADA-USD	DOGE-USD
Count Yes	591	631	468	656	556	550
Count No	3	0	0	2	17	0
Total Diversions	594	631	468	658	573	550

Figure 2. Average Correlation

Convergence and Divergence Analysis

Over the duration of the analysis period, the number of divergences from the long-run average was similar across pairs. Each pair had over 500 total diversions with a high percentage of them returning to the long-run average correlation or better. Ethereum was the most different based on total number of diversions over the analysis period with just 468 total. This is likely due to the fact that the coin is well established and trades in line with the market and Bitcoin in the short and long run. This was surprising given the Non-Fungible Token (NFT) emergence over the analysis period, which would lead Ethereum, the main funding source of NFTs, to trade more on its own. Doge was also on the lower side with 550 diversions, which was surprising given that it is a lesser-known coin as well.

Surprisingly, there were very few instances of the coins not returning to the long-run average correlation. ADA surprisingly had the most; however, all of the failures to return came in the last seventeen days of the analysis. Therefore, it was not given the chance to normalize given the time constraint. This can be considered an outlier, but it is not truly a failure to reconverge that has been given time for reconvergence. Across the pairs, the reconvergence rate was an average of 99.58%, leading to the solidification of the initial hypothesis. Therefore, it can be concluded that the given set of pairs reconverges at a very high rate to normal correlations. Additionally, there were many periods where the pairs decoupled from Bitcoin, leading to a theoretical profit opportunity.

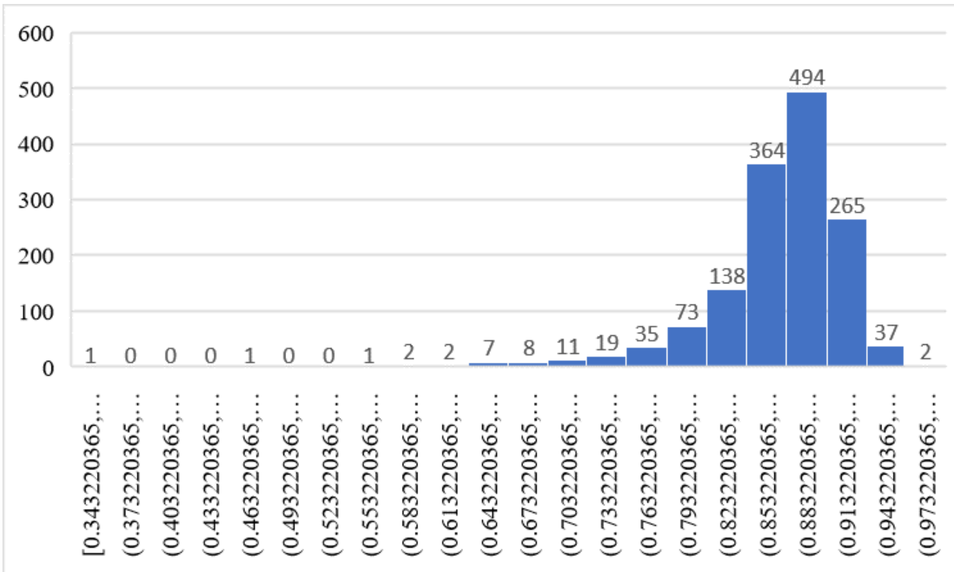


Figure 3. Correlation Histogram

The distribution of correlation from all pairs is unimodal skewed left. The distribution is centered at a mean of .73 which represents a very strong positive correlation. As the figure shows above, the distribution is highly concentrated around the mean and has very minimal outliers in the dataset. The leftmost outlier at ~.34 is from Binance Coin and was during a liquidity run from multiple different cryptocurrencies. Given that Binance Coin is used as a means of exchange on Binance.com with the added benefit of lesser fees and quicker trades, it is extremely exposed to catastrophic cryptocurrency events, especially over the analysis period.

Multi-Scenario Timing Feasibility

```
pairs = ['LTC-USD','XRP-USD','ETH-USD','BNB-USD','HEX-USD','ADA-USD','MATIC-USD','STETH-USD','DOGE-USD']
master = []
towrite = []

for pair in pairs:
  master.append(findCorrelationImproved(pair,5))

for i in range(len(master[0])):
  toAppend=[]
  for array in master:
    toAppend.append(array[i])
  towrite.append(toAppend)

with open('master.csv', 'w', newline='') as file:
    writer = csv.writer(file)

    # Write each item in the list as a new row in the CSV file
    for item in towrite:
        writer.writerow(item)
```

Figure 4. Main Runtime

The above code snippet shows the main running window for the analysis. Although it is very short in terms of line length, the “findCorrelationImproved” function involves many sub-functions and a lot of overall code. Given this snippet, this code could be run in many different scenarios and on many different systems. First and foremost, it could be run using multithreading to analyze different timing and pairs. This code was able to execute analysis of all nine pairs listed in thirty-three seconds given the software and hardware constraints that were explicitly outlined. Therefore, the two other threads that are unused could be used to increase the efficiency and breadth of the analysis. Additionally, this efficiency can be leveraged to support intraday trading prices which involves an exponentially greater amount of data.

Constraint Impacts

Despite the initial hypothesis that the research would be constrained by hardware and software limitations, improvements in the acquisition of the data allowed for exponential increases in efficiency.

```
#old
prices_df = yf.download(crypto_list, start=start_date, end=end_date)["Adj Close"]
#new
prices_df = yf.download(crypto_list, start=start_date, end=today)["Adj Close"]
```

Figure 5. Data Acquisition Improvement

The above figure shows the difference in data acquisition between the beta version of the analysis code versus the final version. Although the difference is very subtle, the first line acquires the data each incremental day. Therefore, it is forced to query a 365-day dataset for each of the correlation coefficients. This is subject to network latency and processing time. The second line downloads all of the necessary data at once, which involves all of the pricing data from the five-year analysis period. From there, the program increments within its RAM to calculate the correlations and make the comparisons. Therefore, the second version only downloads data six times (once per pair), whereas the former line downloads thousands of times per pair. In summary, the second line alleviated the network limitation which would have caused the analysis to take hours rather than seconds per pair.

Storage became a concern after the fifth pair with the allowed amount of maximum RAM being 12gb. This could be solvable by implementing a hybrid model and leveraging the 107gb of hard storage that Google-Colab allows. However, computers are able to access RAM far quicker than solid storage given that it is located closer to the CPU and is not constant. RAM is designed to be storage for the quickest needed data for a system to run, so using the hybrid model could impact the quickness of a large set of pairs. If the RAM were to be expanded, this would be easily fixed, but it would likely come at a major increase in cost which would be exacerbated by the quantity of individual analysis.

Chapter 5 Conclusions

General Conclusions

Based on the results, it can be seen that the given set of pairs does diverge and recouple with the price movements of Bitcoin. Given that Bitcoin currently accounts for ~46.00% of the overall cryptocurrency market (Crypto.com, 2023), it can be assumed that this is likely the root cause of the phenomenon. The altcoins that were selected compose many of the top traded cryptocurrency assets currently, and they have also been available to trade for longer than the analysis period. That is not to say that newer cryptocurrencies do not follow a similar trend, because many new cryptocurrencies are traded with Bitcoin as the liquidity of the pair. Therefore, it would be assumed that Bitcoin dominance would be exerted on these pairs similar to the primitive exchanges that were previously highlighted.

There were many initial predictions for the research that was conducted. The first was that older cryptocurrencies like Ethereum and Litecoin would trend on their own path and not be influenced as much by Bitcoin. This prediction was made on the basis that many of these coins are able to be directly exchanged for real currency rather than using Bitcoin for solvency. However, this was shown to be completely untrue given that Ethereum and Litecoin diverged and recoupled with Bitcoin at a 99.49% and 100.00% success rate respectively. Further research would need to be conducted, but it may be the case that top cryptocurrencies all tend to move together. There is the potential that most coins tend to move in line with this bucket and diverge in the short term. If this is the case, then parallel research could be conducted with almost identical logic to this analysis.

There were multiple catastrophic events that occurred over the five-year analysis period. Initially it was assumed that this could potentially impact individual pairs and lead them to decouple from Bitcoin. However, the results showed the opposite with all coins returning to the dominant trend with over 97.00% success. This was not the expected outcome especially across every pair in the dataset. Although complete decoupling did not occur because of any of these events, it can be assumed that a major crisis may have caused short term decoupling which led to eventual convergence. This turns out to be a positive for the research given that this would display the overarching power that Bitcoin holds regardless of climate.

Proposed System Integration

Based on the results of the analysis, the previously mentioned theoretical trading system could be put in place. The proposed integration would be subject to the constraints that were highlighted, which could be overcome with an institutional budget or further development in the necessary hardware and software. The proposed system will look to capitalize on identifying divergence by making buy and sell decisions during different periods, which was highlighted in a previous section. The system can be broken down into two sections: identification and trade execution. The former can leverage the scripts used to perform this research given that they are cross compatible with intraday data as well. Therefore, the timing can be experimented on with no significant changes in constraints other than the requirement of excess computing power and storage. The trade execution portion would be rather simple with many exchanges having APIs to perform programmatic trades. The trading system would receive instruction from the identification system and execute buys and sells.

Whether or not the system would achieve alpha is still to be seen. There are many issues that programmatic trading systems face, especially in the modern day. From a markets perspective there is always the issue of saturation which derails any hope for alpha derivation. Essentially, the more systems there are trading, the harder it is to gain the upper hand for any individual or system. Therefore, beating the market or specific benchmark is extremely difficult. The system would also encounter the previously mentioned constraints and be heavily impacted by timing. Assuming there is alpha to be realized, the system would have to continue performing identification and execution at an accelerated pace as competing systems enter, and as existing systems advance.

A major perk to programmatic trading is the fact that it eliminates the emotional element of markets. There are many theories surrounding how emotions play a role in market function and trade decisions overall. Breaban and Noussair proposed that fear and exuberance play a key role in market crashes and rallies respectively (Breaban & Noussair, 2015). Furthermore, cryptocurrency is known as a market fueled by speculation which inherently involves a lot of emotion as well. With major rallies and crashes occurring frequently, fear and exuberance would likely be most applicable to this market. Therefore, using a robotic trader that solely focuses on quantitative measures would be a good alternative to manual trading.

Closing Remarks

Despite the initial premonition that Bitcoin and upper market dominance are decreasing in power, it was shown across the selection set that this is in fact false. Furthermore, it was shown that cryptocurrencies, whether they are at the top or bottom of the market, recouple with Bitcoin after being divergent at an extremely high rate. The process of obtaining the data and analyzing it was both interesting and extremely enriching. Perhaps the most interesting points of the project did not even necessarily come from the specific research. The most interesting part was conducting the research under the constraint of any retail investor's free and available resources. Seeing the true power of the resources that are available to the average person promoted a major vote of confidence in future informed investing. Although some of the measures and techniques were very complex, using this research as a baseline could truly push less experienced investors and quantitative analysts to higher highs. In conclusion, the goal of this thesis was to debunk the notion that Bitcoin dominance is fading away, and to show that it could be done by anyone.

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ACADEMIC VITA

SHANE F. O'DONNELL

EDUCATION

The Pennsylvania State University | Schreyer Honors College — **University Park, PA**
Smeal College of Business | Bachelor of Science in Finance — *Aug 2019 – May 2023*
College of Information Systems and Technology | Minor in Information Systems and Technology

RELEVANT EXPERIENCE

Financial Technology Partners — **New York, NY**
Investment Banking Summer Analyst — *Summer 2022*
Payments
- Investment banking summer analyst in the Financial Technology coverage group for 10-weeks
- Member of a deal team on a $5.2 billion acquisition of a global payment processor by a money center bank
- Utilized PowerPoint, Excel, and S&P Capital IQ to analyze comparable companies and precedent transactions

Insurance Technology
- Member of a deal team on a dual process with an interim funding round and potential buyout of an insurance technology startup
- Responsible for performing all investor tracking for the dual process and creation of weekly update presentations
- Collaborated with Managing Director to create and present pitchbooks to potential investors and acquirers
- Collaborated with junior team to update financial models including experience with changes in the debt structure of the Company

Self Employed — **Chalfont, PA**
Sole Proprietor — *Jan 2013 – Present*
Ecommerce
- Operation of five successful online stores using self-coded Shopify based stores with ~30,000 products sold
- Advertised using Google and Meta (Facebook) ads with SEM-rush based research and a return on ad spend (ROAS) of 2.5
- Ranked as a top seller on Etsy with multiple top selling products and over $50,000 in revenue in the first year of operation

Programming
- Created momentum-based equity trading software based on homemade artificial intelligence model using TensorFlow
- Partnered with a Professor to create an API that pulls projected growth rates for equities present in the Professor's research
- Created a Shopify based integration of the PayPal Smart Buttons API that is universally compatible across all stores
- Developed automatic fulfillment software to integrate with Shopify and Etsy to automatically fulfill drop-shipped products

Nittany Lion Fund, LLC — **University Park, PA**
Fund Manager | Financials Sector — *Apr 2021 – Present*
- Served as a Fund Manager of the Financials portfolio valued at ~$1.10 MM within Penn State's ~$13.50 MM student-run hedge fund by completing sector performance overviews and equity pitches with the goal of outperforming the S&P 500
- Created qualitative and quantitative analysis for equities using the discounted cash flow model, dividend discount model, comparable analysis, and ratio analysis with data from Bloomberg, FactSet, and SEC filings

Wall Street Bootcamp — **University Park, PA**
Participant — *Apr 2021 – Present*
- Selected to be a participant in the exclusive Wall Street Boot Camp program which prepares students for a career on Wall Street
- Recipient of Ruby Zhou Scholarship which recognizes students for personal accomplishment on their resume

LEADERSHIP EXPERIENCE

Beemia Start Up — **University Park, PA**
Consultant / Ambassador — *Jan 2020 – May 2020*
- Proposed potential marketing campaigns based on Google and Facebook ads with keyword statistics from SEMrush
- Secured integration deals with local restaurants and managed campus-based marketing efforts

McDonald Elementary Book and Food Pantry — **University Park, PA**
Consultant / Ambassador — *Dec 2017 – Present*
- Managed book and food donations for Warminster community members and local students

ADDITIONAL INFORMATION

Honors: Schreyer Academic Excellence Scholarship, Ruby Zhou Scholarship, Click Bank Affiliate, Quick Start Award
Interests: Michelin Guide imitation cooking, Auto Shows, Vertical Training, Artificial Intelligence (object and speech detection), General programming using web and local based languages, Crab fishing, Surfing, Rock climbing, Personal health