To The Moon: Analyzing the Temporal Relation of Cryptocurrency Prices

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I. Objective

The primary objective of this research project is to conduct a comprehensive analysis of historical data related to Bitcoin (BTC) and other cryptocurrencies, with a specific focus on identifying recurring trends and patterns associated with time intervals such as months of the year or days of the week. By investigating these temporal dimensions and correlating them across different kinds of cryptocurrency, our aim is to provide valuable insights into potential trends in cryptocurrency price fluctuations. This analysis will serve as a valuable resource for investors and individuals interested in strategically buying and selling cryptocurrencies, aiding them in making informed decisions about the timing of their transactions.

II. Motivation

The motivation behind this research stems from the growing prominence of cryptocurrencies as an alternative investment class and a means of conducting financial transactions. Cryptocurrencies like Bitcoin have exhibited unprecedented price volatility, creating both opportunities and risks for investors and traders. Understanding the temporal dynamics influencing these price movements is crucial for mitigating risk and optimizing investment strategies.

Enhanced Decision-Making: By uncovering temporal patterns, we aim to empower investors and cryptocurrency enthusiasts with actionable insights. Armed with knowledge about when cryptocurrency prices tend to rise or fall, individuals can make more informed decisions, whether they are looking to buy, sell, or hold digital assets.

Risk Mitigation: Cryptocurrency markets operate 24/7, which can make them particularly challenging to navigate. Our analysis seeks to identify periods of heightened volatility and stability, helping investors manage risk more effectively by choosing optimal entry and exit points.

Market Awareness: Awareness of how cryptocurrency markets respond to the opening of key global financial centers like New York and Tokyo can be invaluable. This knowledge can help traders anticipate price movements associated with market sentiment shifts, regulatory changes, or economic events in these regions.

Long-Term Investment Strategies: Understanding seasonal trends, such as whether certain months tend to be more favorable for cryptocurrency investments, can assist long-term investors in devising strategies that align with historical performance patterns.

Education and Research: Beyond immediate investment decisions, this research project contributes to the broader understanding of the cryptocurrency market. It fosters a data-driven approach to cryptocurrency analysis, benefiting researchers, analysts, and policymakers seeking to comprehend the evolving nature of digital assets.

III. Preliminary Discussion of the Data

Within this project, we will be looking at historical data on cryptocurrencies. With there being so many different cryptos nowadays we will stick to the main three ones that are the most commonly used as well as the most talked about. These three are Bitcoin, Ethereum, and Litecoin. With the three cryptos that we will run a collection of price trend analyses and other models to reveal if there are any trends or correlations that a trader could take advantage of. The intent is to find any kind of patterns based on simple patterns that could fuel a low-computation trading algorithm.

Due to the rise in prices over time, we are more looking at which would have been a better option over weekly or monthly time periods. This way it can tell us if buying at the beginning of a certain day or month is profitable rather than just buying to hold it for 10+ years as many people who were early adopters of cryptocurrencies sold most of their crypto before it became worth as much as it did. The overall goal is to just see if there is any promise of buying at a certain time versus another and not holding onto them on for days.

Thanks to Historical data we are able to see the open, close, high, and low price of each day going back five years. With five years of data, we should be able to see if there is a trend within this. The cryptocurrency markets are open 24 hours a day and 7 days a week, so it becomes a bit difficult to define a true open and close like other national stock exchanges would hold. The crypto market open is set at 00:00 am as the beginning of the day. Close is often referred to as the end of the range and is marked at 23:59 pm. We must take this into account when dealing with these numbers as they do not behave exactly like other markets.

IV. Background

Many researchers have done something similar to this by looking at the S&P 500 in order to see if there was a better way to invest than just leaving your money in the stock market. What The Bespoke investment group found was that buying at the close and selling at the open would lead to an 1100% increase compared to buying at the open and selling at the close has led to a 20% loss in money. With this idea, we went to see if something like that could exist for cryptocurrencies as they have become more and more common (Udland). You can see this trend in the graph below.

Fig. 1. S&P Open vs Close Graph

This sort of analysis was an inspiration behind the cryptocurrency analysis of our study, creating a trading algorithm based on simple parameters. With all of us having some kind of interest and crypto and more knowledge of it than most people we went on to see if exists in any way with BTC, ETH, or LTC.

V. Approach

Our approach to this, as stated, was to take a few years of data for the 3 more popular cryptocurrencies. Thankfully historical data was easy to obtain from Yahoo Finance which allowed us to go back to 2015 for litecoin and Bitcoin, but only November of 2017 for Ethereum.

With this data available in a CSV format, we had to go through and parse out everything we did not need including some things such as the high and low of each day. As those are unpredictable, especially on a single day, we stripped this data out to use in the rest of our analysis. With this, we could just have our Open and Close prices as well as the day each of those corresponds to utilization.

Beginning with bitcoin (BTC), we ran each kind of cryptocurrency through various models and analyses, focusing on the daily returns which means a position that was bought at the open, held for 24 hours, and sold at the close. We analyzed the daily returns on various time frames such as days of the week and months of the year.

After running analysis on the individual currencies, we combined them in order to infer any further trends or correlation in the data. By performing these calculations and running through these models, we began to see a trend in how investing like this may work in the real world exactly as Bespoke investment did with the S&P in the 1990's.

VI. Data that was utilized

- Obtained - The data obtained was historical data available on the Yahoo Finance website for BTC, LTC and Ethereum. With the obtained data we are able to parse it out and convert this into some type of metric we can better understand.
- Processed - Processing the data. we stripped out all the useless information included with the prices such as High, Low and daily volume of each coin.
- Integrated - We integrated the different prices for the different types of cryptocurrency into combined data frames using Python code in order to create models that graphed certain price trends and correlations.
- Validated - This data has been provided by Yahoo finances and is validated by comparison to other sources like Wall Street Journal which has similar numbers.

VII. Results

Through analyzing this rich data, certain trends began to immediately reveal themselves. We ran the data through a large amount of different kinds of models. When investigating the relation between prices and temporal dimensions, we began with the weekly scale. The results are shown below.

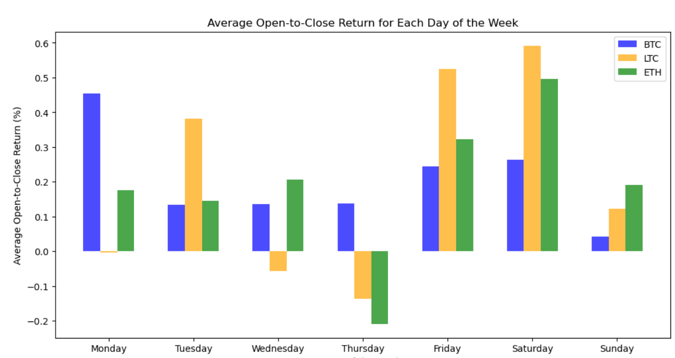

Fig. 2. Daily Return by Day of the Week. Averages are based on buying at 00:00 am and selling at 23:59 pm. This data is aggregated over all available years

From this data we can infer that different days are more profitable to day trade on depending on the currency to some degree. Bitcoin's most profitable day on average is a Monday while Litecoin and Ethereum both perform best on Saturday, followed closely by Friday. A possible explanation for this is that due to the cheaper price of these cryptocurrencies, more amateur day traders are trading them and their best hours are going to be outside of the regular work week. Sunday is the least profitable for Bitcoin, although Thursday proves worst for LTC and ETH.

Moving forward from the days of the week, we zoomed out to look at the scope of a whole year, asking which months would be the best to trade in. This means buying the crypto at the beginning of the month and selling at the end. The following results were recorded.

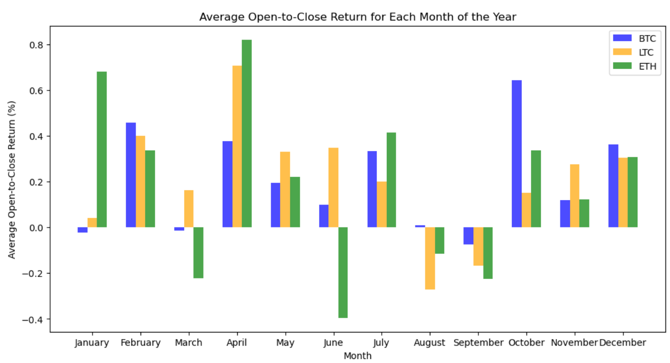

Fig. 3. Best Return by Month.

Once again, we see a correlation between the profitability of LTC and ETH while Bitcoin performs similarly but peaks at a different month. April proves most profitable for LTC and ETH, while October is the best month to hold a position on Bitcoin. September is the worst performing for Bitcoin, losing money on average. Overall, September is a bad month for all three currencies, although August is the worst for LTC and June is the worst for ETH. Further analysis and research would have to be performed to identify the underlying cause of these trends.

Several other trends were analyzed on the temporal dimension but will not be mentioned in this report as they did not provide useful information. Once these models were complete, we began to look at the prices of cryptocurrency related to each other. The following graph shows the prices of each cryptocurrency over the historical period.

This, however, produces a difficult graph to read. The problem lies in the fact that these prices are wildly different in scale with LTC measuring in the 0-100 range in bitcoin measuring in the tens of thousands. In order to work around this, we decided to normalize the prices in order to see the trends more clearly. The results of this are shown below.

This reveals just how closely the prices follow each other. Likely, Bitcoin is the main mover due to its volume of trades, while LTC and ETH are the 2nd and 3rd place cryptocurrencies that largely follow the overall sentiment of Bitcoin. This is reinforced by the correlation matrix. Firstly, all 3 have a strong correlation with each other, having a minimum correlative strength of 0.58 between LTC and ETH. Both LTC and ETH have a strong correlation with BTC, however. Seeing that these trends were largely shared between the top 3 cryptocurrencies, we further decided to investigate reasons to choose one over the other. A measure of volatility was taken and the results are shown here.

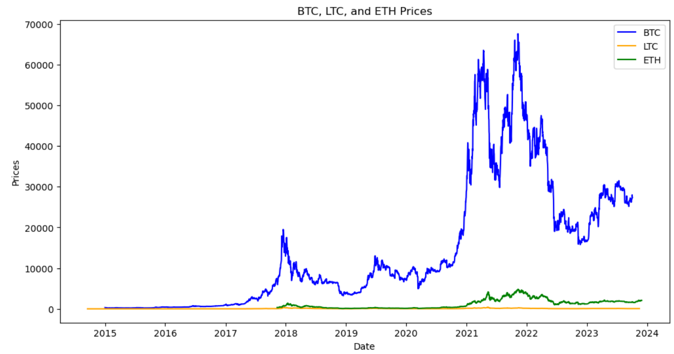

Fig. 4. Prices of each cryptocurrency over time

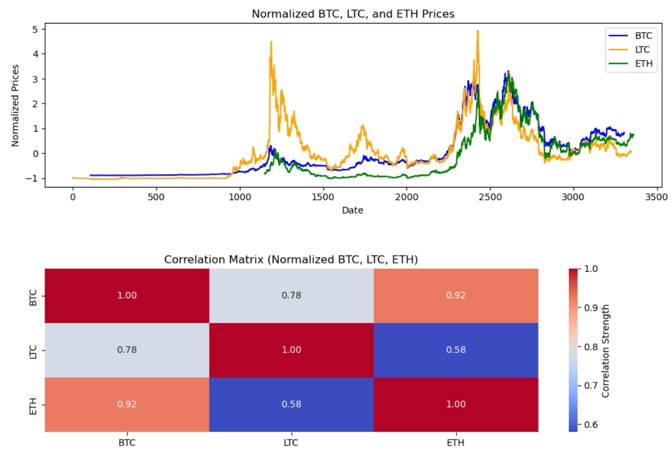

Fig. 5. Normalized prices of cryptocurrencies and correlation matrix between their prices

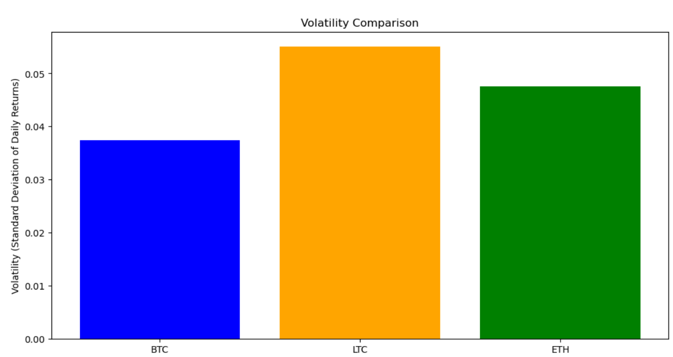

Fig. 6. Average Volatility of Top 3 Cryptocurrencies

What this information means is that LTC will experience the greatest fluctuation of price on average when compared to the other currencies. This makes sense as the price is still relatively small, so even a smaller increase or decrease in price would constitute a greater percent change in this smaller stock. With this model, we could look into predicting possible profitable days, weeks, or months.

The final task we attempted was to create a classifier trained on this historical data to try and predict if any given day was going to be profitable or not. The following results of this model are shown below.

```
Model Accuracy: 0.78
Classification Report:
              precision    recall  f1-score   support

           0       0.76      0.76      0.76       295
           1       0.79      0.79      0.79       345

    accuracy                           0.78       640
   macro avg       0.78      0.78      0.78       640
weighted avg       0.78      0.78      0.78       640
```

Fig. 7. Results from classifier trained on BTC historical data

This was a basic attempt at implementing a machine learning model. The results look promising though they may be a bit misleading. A model that predicts if a trade is good with 0.76 precision seems very promising, yet when you look at the historical upward trend of data, any random guess is going to be more likely to be profitable given the astronomical skyrise in crypto currencies since 2015. We have clearly already passed this nonstop climb, so this model is less likely to be useful when predicting current data, and the volatility of cryptocurrency could make this dangerous.

VIII. Primary issues encountered during the project

The primary issue that we encountered was regarding the available data. A type of analysis that we would have liked to perform was to analyze the cryptocurrency market prices as they relate to the opening and closing times of different markets around the world such as the US market or the Japanese market. Unfortunately, historical data for cryptocurrency labels the open and close for these prices as the beginning of the day at 00:00 am and the end of the day at 23:59 pm.

With no way to assess what a cryptocurrency's price was in between the close and open at specific points on a large scale, we were required to pivot away from this goal. However, we were still able to adjust our goals while still aligning with our original objective to pursue trends and relationships between price and different time intervals such as days of the week and months of the year.

IX. Future Work

With everything said, some of the future work we may like to work on would be some type of machine learning. This is so that we can train a model with our current data and gather more data to be used for the model. Additionally with this model, we would also like to analyze if there are months or times of year when cryptocurrencies tend to be the most profitable

With machine learning and predictive analysis advancing every day, our future work aims to enhance the accuracy and depth of the forecasts for cryptocurrencies. By using new algorithms and techniques, we plan to analyze the complex patterns that appear in the price movements through statistical methods. The models would be trained on extensive historical data that we have already collected and shown here which would allow them to learn and adapt to the nuances of the market behavior for these cryptocurrencies.

We could use this to explore the use of recurrent neural networks (RNNs) and long and short-term memory networks (LSTMs). which are particularly adept at handling time-series data like cryptocurrency prices. This would enable us to not only predict future price trends with greater precision but also identify potential market anomalies and price corrections that occur within any market.

Integrating our research with machine learning models gives us hope that it could unveil deeper insights into the dynamic and often unpredictable work of cryptocurrencies. This would ultimately aid investors and analysts in making informed and strategic decisions on when to buy or sell these cryptocurrencies.

On top of the challenging task of creating a large machine learning model for this analysis. Some other simple work we would like to do is to just look into more cryptocurrencies to gather more data and to also see if we would end up having the same trends across multiple different cryptocurrencies.

X. Org Chart: Timeline and Responsibilities for each member

A. Timeline

1) Data Selection - Oct. 1st
   - Collect all the data required to feed the model.
2) Data Cleaning - Oct 15th
   - Data will need to be cleaned and formatted so that it will work within the developed model.
3) Build Model using Python - Oct 21st
   - Complete the model that will be used to analyze cryptocurrency prices in relation to specific temporal dimensions, eg. time of day, day, month, year.
4) Analyze Results - Oct 28th
   - Results obtained from the model will need to be analyzed for any patterns.
5) Draw Conclusions - Nov 1st
   - Once results have been analyzed, we must draw conclusions and find any market insight based on the results retrieved.
6) Create Diagrams - Nov 7th
   - Patterns from the results will best be represented in visual format. This will also be the key element of the presentation to the class

7) Finish Report - Nov 30th
   - An overarching compilation of all the parts of the project in written form. Includes Introductions, Objectives, Methodology, Results, and Conclusions.
8) Finish Presentations - Dec 3rd
   - A PowerPoint presentation that combines the figures produced from the "Create Diagrams" milestone with key components of the report to create a succinct and informative overview of our project to other students.

B. Team Responsibilities

The responsibilities of each team member are detailed below with the understanding that some roles have adapted as the progress developed. Members stepped in and helped whenever required or requested regardless of assigned roles.

- Kellan Christ - Coordinator
  - The coordinator sets forth the individual tasks for each member and insures that they are meeting deadlines for these tasks. The coordinator is the visionary of the project, and in the case of this team, the coordinator is the one who created the initial project objective. The coordinator is expected to take a leadership position and intuit the necessary work to be done. Kellan also assisted with the written report.
- Cory Headrick - Monitor
  - Besides the monitor task as defined at the beginning of the class, Cory worked on the code, models and analysis, implementing the designs and direction set forth by the coordinator. Cory assisted with completion of the written report.
- Kevin Craddock - Recorder
  - Besides the recorder role as defined at the beginning of the class, Kevin also worked on the code and analysis alongside Cory. Kevin was also responsible for putting together the presentation.
- Logan Bowers - Checker
  - Besides the duties of the checker, Logan also performed analysis and interpretation of the models and analysis provided by Cory and Kevin. Logan also assisted with the presentation of the information.

XI. SOURCES

Udland, Myles. "Buy the Close, Sell the Open." Yahoo! Finance, Yahoo!, finance.yahoo.com/news/buy-close-sell-open-114705554.html. Accessed 28 Nov. 2023.