Determining the profitability of technical chart patterns on cryptocurrency markets

Word count: 4,567

AP Capstone Research

April 26, 2024

INTRODUCTION

"The stock market is a key pivot in every growing and thriving economy, and every investment in the market is aimed at maximizing profit and minimizing associated risk. As a result, numerous studies have been conducted on the stock-market prediction using technical or fundamental analysis…" (Kofi Nti 1) Kofi Nti, a professor at the University of Cincinnati, further argues for the importance of studying markets as "the well-being of every growing economy, country or societ[y] in this twenty-first century mainly hinges on their market economies and stock-price, with the financial market being the pivot. Thus, it is essential and vital to study and learn about the financial market extensively." (Kofi Nti 2) A key emerging financial market necessitating further study is crypto. While most studies into crypto either focus on fundamental or complicated forms of technical analysis, past empirical evidence hints that simpler forms of technical analysis could prove profitable. Yet predictive chart patterns, the simplest form of technical analysis, have not been rigorously studied as a trading strategy for cryptocurrencies. This study aims to fill that gap by testing chart patterns' profitability in crypto markets.

The focus of this study is to evaluate the profitability of the best performing technical chart patterns in the five largest cryptocurrency markets using a two-month backtest.

LITERATURE REVIEW

Technical vs. fundamental analysis

The strategies that investors use to maximize profits and minimize risk can be categorized into two groups: fundamental and technical strategies. "[Fundamentalists] argue that the price of a share of stock is based almost exclusively on the value of the company whose securities are in question." (Pinches 104) Robert Levy, a faculty member at American University, explains the process as: a “fundamentalist relies upon economic and financial statistics and information. He investigates corporate income statements, balance sheets, dividend records... Taking all these factors into account, he projects corporate earnings… to arrive at the intrinsic value of the security under observation. He then compares this intrinsic value to the existing market price and, if the former is sufficiently higher, he regards the stock as a purchase candidate” (Levy 83) They operate under the assumption that actual prices tend to move toward intrinsic value, therefore “determining the intrinsic value of a security is equivalent to predicting the security's future price.” (Levy 83)

Rather than aggregating information to value a company, technical analysis focuses on the stock itself. “Technical analysis deals with forecasting probable future price action by a study of past price action.” (Tabell 70) “It refers to the study of the market itself as opposed to the external factors reflected in the market. Technical analysis is, in essence, the recording of the actual history of trading for one stock or group of equities, and deducing the future trend from this historical analysis.” (Levy 83) It’s underpinned by the assertion that markets tend to move in trends dominated by supply and demand forces, which determine whether there are more people buying or selling an asset. (King 324) “It is not important to know why either buyers or sellers are in the majority-all that is necessary is to know that such is the case and align oneself accordingly” (King 324)

Investors use a variety of tools to determine supply and demand relationships within a security including “bar and point-and-figure charts, confidence indices, odd-lot data, short interest ratios, advance-decline figures, volume, [and] statistics on new highs and lows…” (Pinches 105) While these tools indicate when to buy or sell an asset, they give no information about what shifted momentum. The lack of an explanatory quality has led economists to qualify the usability of technical indicators through theoretical models and empirical studies.

Efficient Market Hypothesis (EMH)

The most prominent model used for the dismissal of technical analysis is the Efficient Market Hypothesis (EMH). Proposed by Nobel Prize winner and economist Eugene Fama, it states that "...security prices at any time 'fully reflect' all available information" (Fama 383) EMH can be subdivided into three categories that better define the set of information said to be "fully reflected". However, all of these categories include historical price data, and therefore in all of these "...early treatments of the efficient markets model, the statement that the current price of a security "fully reflects" available information was assumed to imply that successive price changes are independent" (Fama 386) Assuming independence sets EMH in direct antithesis with technical analysis because "Independence implies, of course, that the past history of a series of changes cannot be used to predict future changes in any 'meaningful' way" (Fama and Blume 226)

Fama and Blume backed their theoretical findings with a statistical study on the use of filter rules, a type of technical analysis, on New York Stock Exchange (NYSE) stocks. Studying 31 different stocks across two years, they found that only four stocks produced profits after considering commission, and none proved more profitable than a simple buy-and-hold strategy when considering commission and transaction costs. (Fama and Blume 233) Their findings conclude that "the market is working rather efficiently from an economic viewpoint." (Fama and Blume 240)

Fama and Blume formalize and support a theoretical model denouncing technical analysis, but the literary discussion continued as there is a wide range of technical indicators they did not test, practitioners still employed technical strategies to varying degrees, and EMH's assumption that markets react immediately to new information is an oversimplification.

Alternative interpretations and theoretical models

Alternative models challenge the way EMH handles new information. Noisy rational expectation models suggest an uneven dissipation of new information. Herding and agent-based models suggest that market actions deviate from expected reactions.

Following a noisy rational expectation model, Treyner and Ferguson propose that a trader gains access to non-public information. (Treyner and Ferguson 761) They define a Markovian process to describe when others will learn this new information, and subsequently construct a probability distribution for the market's reaction. (Treyner and Ferguson 765) By computing probability values, they show "that past prices, when combined with other valuable information, can indeed be helpful in achieving unusual profit" (Treyner and Ferguson 773) Brown and Jennings, researchers from Indiana University, corroborate their findings by extending the model to two time periods (Brown and Jennings 542) In the second period, "investors use the historical price in determining time 2 demands because the current price does not reveal all publicly available information provided by price histories…" (Brown and Jennings 543) These two studies conclude that, if a noisy rational expectation model is correct, information is contained within price histories and therefore "technical analysis does have value." (Brown and Jennings 542)

The herding model, proposed by economists Froot, Scharfstein, and Stein, proposes "positive informational spillovers: as more speculators study a given piece of information, more of that information disseminates into the market, and therefore, the profits from learning that information early increase." (Froot, et al. 22) This quality gives rise to market depth parameters that depend on the covariance of fundamental and non-fundamental information, giving rise to a scenario where “both chartists [technical analysts] and fundamentalists submit positive market orders and earn positive expected profits.” (Froot, et al. 20) In this case, the more trades based on technical analysis, the more profitable technical strategies become. Schmidt, a professor of economics at the University of Munich, arrived at the same conclusion by applying an agent-based model, which “showed that if technical traders are capable of affecting market liquidity, their concerted actions can move the market price in the direction favorable to their strategy.” (Park and Irwin 15)

Alternative models support the adoption of technical analysis, however, “[EMH] still seems to be a dominant paradigm.” (Park and Irwin 16) Despite EMH’s prevalence, economists from MIT and Wharton, ran a “specification test based on variance estimators” to find that “the random walk model is generally not consistent with the stochastic behavior of weekly returns…” (Lo and Mackinlay, 42) Their findings conclude in the rejection of the random walk hypothesis, a quality emerging from EMH. (Lo and Mackinlay 61) The study does not disprove EMH, as “the rejection of the random walk model does not necessarily imply the inefficiency of stock-price formation,” but it does suggest its incompleteness. (Lo and Mackinlay 61)

EMH has been challenged by alternative theoretical models and studies qualifying its properties, however economists cannot agree on a better model for security pricing. “Hence, sharp disagreement in theoretical models makes empirical evidence a key consideration in determining the profitability of technical trading strategies” (Park and Irwin 16)

Empirical studies supporting technical analysis

Various empirical studies have shown that technical analysis, particularly chart patterns, can be profitable in financial markets. Robert A. Levy conducted the first study of chart patterns on NYSE stocks, in which 32 five-point patterns were tested on 548 securities across five years. (Levy 316) He detected the patterns 19,077 times, of which 9,383 were followed by a breakout and further processed, and found that none of the 32 patterns “performed very differently from the market.” (Levy 318) Although no significant profits were made in this period, seven patterns produced greater than 10% returns before transactional costs. (Levy 320) These results allude that technical chart patterns could prove useful in financial markets with lower transaction costs.

Lo, Mamaysky, and Wang subjected 10 chart patterns, including head-and-shoulders, broadening tops and bottoms, and triangle tops and bottoms, to a goodness-of-fit test on daily returns of individual NYSE/AMEX stocks between 1962 and 1996. (Lo, et al. 10-15) They find that “technical patterns do provide incremental information, especially for NASDAQ stocks,” (Lo, et al. 24) “where all 10 indicators showed overwhelming significance.”(Lo, et al. 22) While this study does not prove “that technical analysis can be used to generate ‘excess’ returns, it does raise the possibility that technical analysis can add value to the investment process.” (Lo, et al. 24)

Chang and Osler bolster the empirical argument for technical analysis’ profitability by applying a head-and-shoulders pattern to foreign exchange rates between the Canadian dollar and different currencies. (Chang and Osler 641) They find this strategy leads to a 13% annualized return for the Canadian dollar to Mark exchange and a 19% annualized return for the Canadian dollar to Yen exchange. (Chang and Osler 648) Both of which are significantly higher than the benchmark S&P 500 growth of 6.8% for the year. (Chang and Osler 648)

Empirical studies support the fact that technical analysis, particularly chart patterns, can be significantly profitable in certain financial markets.

Conditions for the applicability of technical analysis

A survey study conducted by Menkhoff and Taylor on foreign exchange professionals finds that over 90% of foreign exchange traders use technical analysis to some extent, and then provides a series of stylized facts demystifying where technical analysis should be profitable. (Menkhoff and Taylor 941)

They found that "the relative weight given to technical analysis as opposed to fundamental rises as the trading or forecast horizon declines." (Menkhoff and Taylor 941) Also, "the consideration of transactional costs and interest rate costs actually faced by professionals does not necessarily eliminate the profitability of technical currency analysis," (Menkhoff and Taylor 946) which is true only for alternative markets as opposed to the NYSE. They further find that "technical analysis tends to be more profitable with volatile currencies." (Menkhoff and Taylor 947) And that the profitability of technical analysis on high-frequency trades has mixed results, (Menkhoff and Taylor 949) where "time-varying risk premia might explain some of the excess return of technical analysis but not all or even most of it." (Menkhoff and Taylor 953) All of these conditions, including shorter trading periods, alternative markets, higher volatility, and high frequency trading, are factors that increase risk. Yet the increase in risk alone does not fully account for the increased profitability of technical indicators. Therefore, it can be concluded that technical analysis has a higher probability of profitability in riskier portfolios.

Through evaluating the profitability of technical trading rules in Asian stock markets, Bessembinder and Chan find an additional quality that makes technical trading profitable. They "find the rules to be quite successful in the emerging markets of Malaysia, Thailand and Taiwan. The rules have less explanatory power in more developed markets such as Hong Kong and Japan." (Bessembinder and Chan 1)

Both of these studies put forth conditions and characteristics of markets where technical trading rules should generate excess profits. The optimal scenarios for technical rules are short periods of high frequency trades on volatile, risky currencies in alternative, emerging markets.

Cryptocurrency markets and their characteristics

An emerging market that satisfies the proposed conditions, and is therefore a prime candidate for testing technical strategies, is the cryptocurrencies market. Liang and Li define it as "a kind of digital currency in which blockchain is used as a decentralized ledger to secure the transactions and control the generation of new units of currency, which is operated independently without a central authority." (Liang, et al. 1)

The first condition that crypto satisfies is being an emergent market, since the first crypto only emerged in 2009. (Liang, et al. 1) Emergent markets are defined to be relatively new, and compared to the stock market, which started in 1792, crypto is relatively new. It is also considered volatile, since the market is still under rapid development, which makes prices change drastically (Liang, et al. 1) Crypto is also an extremely risky asset; "besides market risks, there also exist shallow market problems, adversary risks, transaction risks, operational risks, privacy-related risks, and legal and regulatory risks." (Liang, et al. 1) Additionally, "Cryptos are traded in decentralized markets 24/7," (Desagre, et al. 1) making short periods of high frequency trading even more accessible than on standard markets. Crypto has demonstrated to possess all the qualities that increase the profitability of technical analysis, which has led to its proliferation in the technical trading literature.

Empirical studies of technical analysis on crypto markets

Recent empirical studies have focused on employing advanced technical strategies, which are typically enhanced by Artificial Intelligence (AI), to trade currencies in the crypto market.

These studies conclude that there are significant profits generated by employing technical analysis on cryptocurrencies.

A group of Brazilian researchers has focused on utilizing machine learning, particularly reinforcement learning and deep learning methods, to generate technical algorithmic trading patterns. (Felizardo, et al. 1) They find that adopting the ResNet architecture yields significantly better performance in trading staple cryptos such as Bitcoin, Litecoin, Ethereum, and Monero. (Felizardo, et al. 1) Researchers at the University of Paris-Saclay also leveraged deep learning to generate algorithmic trading patterns and found that "[their] prediction models using the machine learning approach trained on the Binance cryptocurrency exchange can create profits that are better than the classic Buy-and-Hold strategy and provide much better precision than random guesses." (Goutte, et al. 12)

Other strategies, which do not use AI, have also been tested on crypto markets with similar results. A group of students at Carnegie Mellon University tested nine complex technical strategies to conclude that a combination of exponential moving averages and Heikin Ashi candles produced the best results, with 4.02 winning trades for every losing trade. (Gazizova and Agcaoili 5) Other strategies they tested also had average percent gains for winning trades of over 1,900%. (Gazizova and Agcaoili 7) These results further support the case for technical analysis' profitability in cryptocurrency markets.

Gap

After the initial dismissal of technical analysis through EMH, new theoretical models incentivized empirical statistical studies which proved that chartist strategies could be profitable in certain market conditions. A comprehensive survey of these studies then condensed the characteristics that a financial market must possess for it to allow profitable technical strategies.

An emerging market that possesses these qualities is crypto, so recent studies have focused on and proven the profitability of technical strategies on cryptocurrencies. These studies employ convoluted forms of technical analysis, sometimes even involving AI, but simpler forms, such as chart patterns, have not yet been evaluated in the crypto space. This paper aims to address that gap by evaluating technical chart patterns' profitability in cryptocurrency markets.

RESEARCH METHOD

Purpose of method

Technical pattern's profitability in crypto markets is evaluated through the predictive ability of said patterns on future cryptocurrency price movements. The chart patterns used consist of five points that, if present consecutively on a historical chart, predict whether the price will increase or decrease during the next movement. Their predictive ability is tested on the five cryptocurrencies with the highest market cap and volume. Profitability refers to a pattern's ability to yield returns in excess of a simple buy-and-hold strategy. Buy-and-hold is defined as the net returns of buying an asset at the beginning of the time period and selling it at the end, with no other action.

Backtesting

The profitability tests are conducted via a backtest, which refers to the use of predictive models on historical data; it assesses the viability of a strategy by seeing how it would have performed retrospectively. Investopedia, a peer-reviewed financial blog, explains "The underlying theory is that any strategy that worked well in the past is likely to work well in the future, and conversely, any strategy that performed poorly in the past is likely to perform poorly in the future." (Investopedia) Ronald Kahn, a managing director at BlackRock, further explains backtesting as "requir[ing] that investment decisions at an initial time depend only on information available at that time. Then, given a portfolio at an initial time, the backtest examines the portfolio return between that initial time and a later time." (Kahn 17) The method of backtesting was chosen given the quantitative nature of technical chart patterns, the availability of historical cryptocurrency price data, and its stature as the most widely accepted method to test predictive trading strategies.

Choice of cryptocurrencies

The backtest is performed on the five cryptocurrencies with the largest market cap. Market cap is calculated by multiplying the price per coin of a given crypto by the total number of coins available, and it represents the total value of a given cryptocurrency. Since the market cap is an indicator of value, it was used to filter cryptos based on which ones can be traded like assets. Due to the recency of cryptos, there is a current lack of regulatory oversight for creating one. Therefore, some cryptos are created with no underlying asset or value. These cryptos are of no interest for this study, as technical chart patterns are meant to predict future prices of securities with real underlying value. Patterns are not fitted for small-cap cryptos with no real value, which behave more chaotically but always trend to zero and are more difficult to place trades on due to a lack of volume.

On the contrary, larger cap cryptos have a proven value and higher volumes, which facilitate trades in short time periods and better emulate regular stock movements. This similarity and relative stability provide a solid foundation for testing technical chart patterns. Lastly, cryptocurrencies tracking the U.S. dollar are ignored because of their lack of price movements, as they always stay pegged to the dollar. The five cryptocurrencies with the largest market cap, and therefore the best fitted for this study, are Bitcoin, Ethereum, BNB, Solana, and Lido Staked.

Choice of technical chart patterns

The five chart patterns tested on these cryptos are called descending channel, sloping head and shoulders, ascending channel, bullish pennant, and inverse head and shoulders. Levy found these patterns to have the greatest predictive ability for traditional stocks. He tested the predictive ability of 32 five-point chart patterns on 548 NYSE securities over the span of 5 years. (Levy 316) Through a backtest, Levy ranked these patterns by absolute rate of return before transactional costs, and the top performing ones are labeled "13254, 14253, 14352, 15243, and 15342." (Levy 320) The patterns, which are most commonly known by the names above, were chosen because of their relative success compared to other technical chart patterns,

Choice of time period

Now that the strategy and data are defined, the last element of the backtest to specify is the time period. The five most profitable technical chart patterns are tested on the five largest cryptos over a period of two months. The test will span from February 24st, 2024 to April 21st, 2024, within which crypto prices will be recorded in fifteen-minute intervals. The time span was chosen because the Python API (application programming interface) used to retrieve crypto price histories, yFinance, only has intraday price information for 60 day intervals. The study focuses on intraday trading periods rather than spanning a longer time frame due to technical analysis' increased useability in shorter time periods. These parameters will still yield a total of 136,800 price data points between all the cryptos, which gives a modest sample size adequately representative of typical crypto price movements, and therefore a fairly accurate assessment of the chart pattern's profitability.

Backtest implementation

A computer program runs the backtest and returns its results. The Python programming language is used as it has the most amount of libraries available to retrieve, store, and analyze data. The libraries in use are yFinance, which retrieves crypto price data from Yahoo Finance, pandas, which is a data analysis tool used for storing the retrieved price data, and numpy, which speeds up the numeric operations used in pattern recognition.

The program backtesting will implement counters for the number of times each chart pattern arose and how many times it was successful. Each time a pattern appears, the program also records the possible profits if it is successful and the possible losses if it is unsuccessful. For each pattern in each crypto, it will return the number of times it appeared, the number of times it was successful, the aggregate returns, and the baseline returns of buy-and-hold during the same time period. The success rate is calculated by dividing the number of times a given pattern correctly predicted future price movements by the number of times it appeared. The total returns are calculated by aggregating the revenues from each time a given pattern was successful and the losses from each time a given pattern was unsuccessful. Buy-and-hold returns are used to assess if a given pattern was able to generate excess returns. The sign of the aggregate returns number indicates whether a pattern is profitable and its performance compared to buy-and-hold indicates whether it is profitable enough to be worth implementing.

FINDINGS

Aggregate results

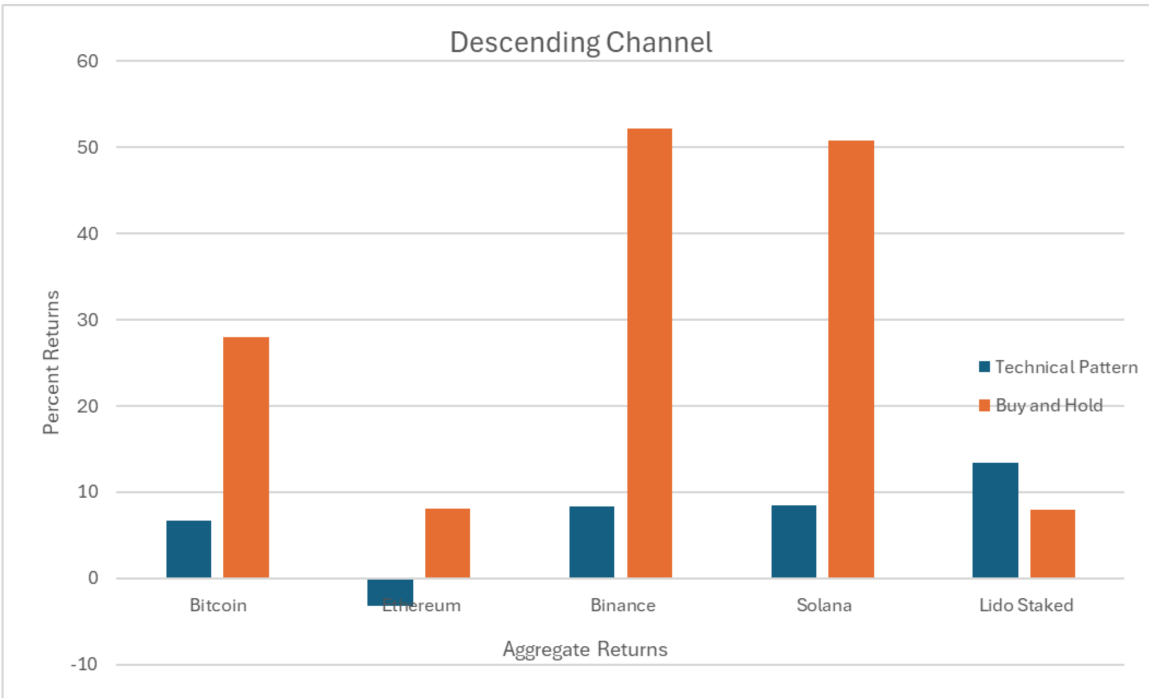
The backtest resulted in a total of 25 possible investment strategies, stemming from the permutations of five technical chart patterns across five cryptocurrencies. Through these strategies, 4,185 patterns were identified, of which 2,109 correctly predicted the next price movement. The total reveals that the technical chart patterns were accurate 50.39% of the time.

Of the individual patterns, 18 yielded positive returns, 13 returns greater than 5%, 6 returns greater than 10%, 3 returns greater than 15%, and 2 returns greater than 20%. Although most patterns returned positive profits, only 4 achieved greater returns than a simple buy-and-hold strategy. The three best performing patterns were the bullish pennant on Ethereum, profiting 23%, inverse head and shoulders on Solana, profiting 23%, and bullish pennant on Binance, profiting 18%. The three worst performing patterns were sloping head and shoulders on Bitcoin, losing 5%, descending channel on Ethereum, losing 3%, and inverse head and shoulders on Binance, losing 3%.

Next, each trading strategy's performance is more closely evaluated across individual cryptocurrencies.

Pattern 1: Descending channel

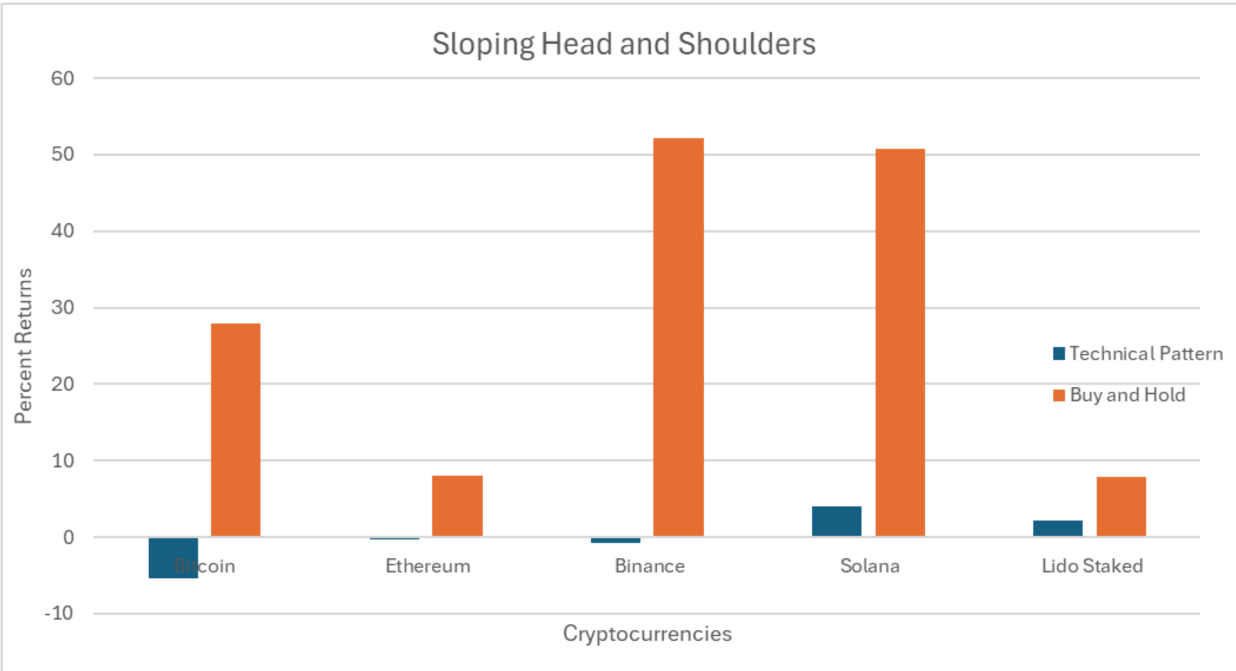
Figure 1: *Percent Returns for Descending Channel and Buy-and-Hold Strategies, Grouped by Cryptocurrency*



Descending channel patterns appeared a total of 935 times and accurately predicted future price movement 48% of the time. It performed best for Lido Staked, where it earned 13%, and worst in Ethereum, where it lost 3%. Notably, it performed better than a buy-and-hold strategy for Lido Staked and posted profits greater than 5% for all but one crypto.

Pattern 2: Sloping head and shoulders

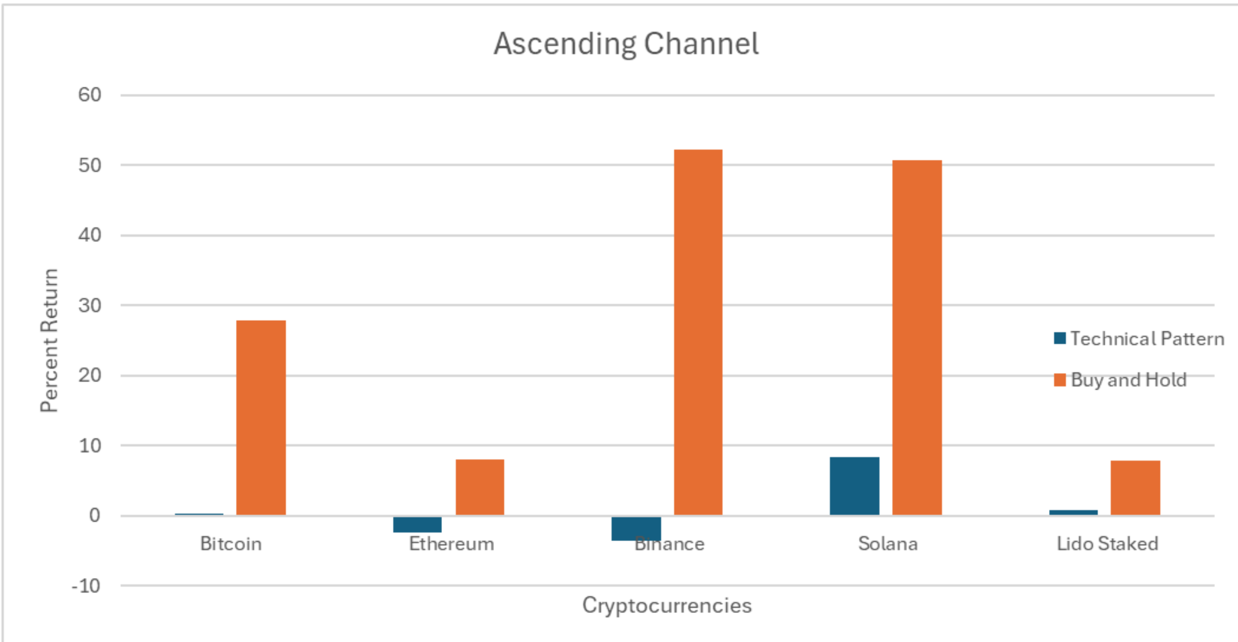
Figure 2: *Percent Returns for Sloping Head and Shoulders and Buy-and-Hold Strategies, Grouped by Cryptocurrency*



Sloping head and shoulders patterns appeared 261 times and was accurate 46% of the time. It performed best for Solana, gaining 4%, and worst for Bitcoin, losing 5%. This pattern produced net losses for 3 out of 5 cryptos and had the worst performance of a single pattern crypto combination. It also resulted in the least amount of trades

Pattern 3: Ascending channel

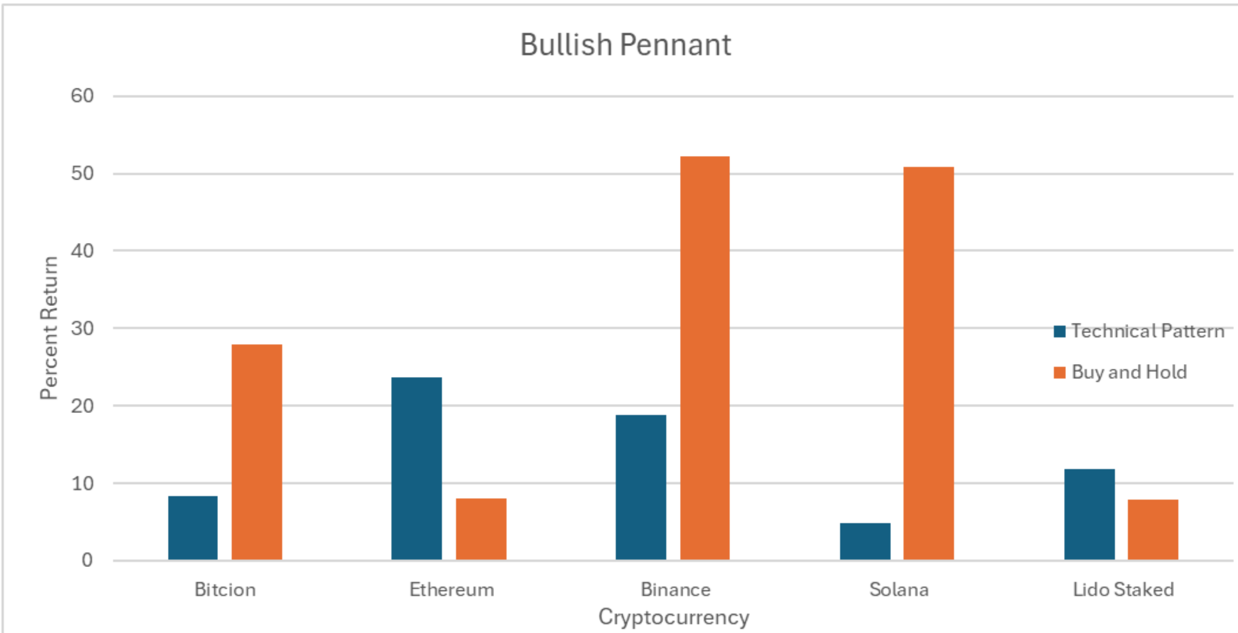
Figure 3: *Percent Returns for Ascending Channel and Buy-and-Hold Strategies, Grouped by Cryptocurrency*



Ascending channel patterns showed up 379 times and correctly predicted future price movements 45% of trades. It performed best for Solana, gaining 8%, and worst for Binance, losing 3%. It resulted in net losses or profits less than 1% and made mostly incorrect predictions for all but one crypto.

Pattern 4: Bullish pennant

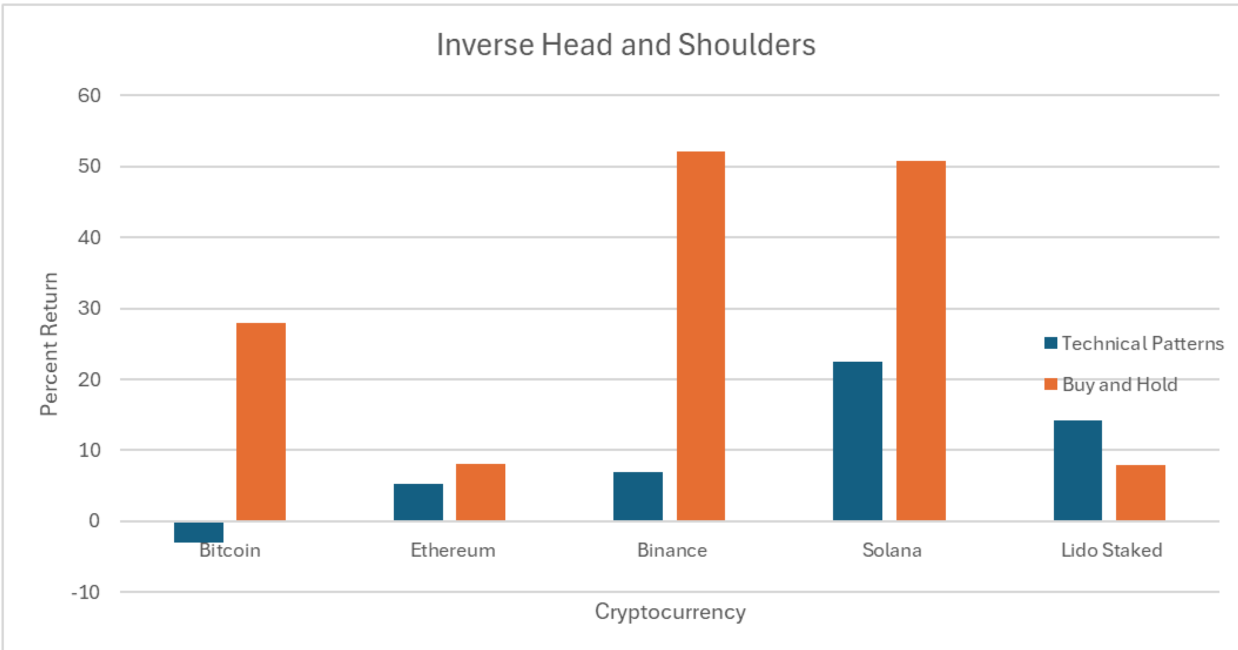
Figure 4: *Percent Returns for Bullish Pennant and Buy-and-Hold Strategies, Grouped by Cryptocurrency*



Bullish Pennant was the most abundant, appearing 1517 times, and correctly predicted the next price movement 49% of trades. It performed best for Ethereum, with a net profit of 23%, and worst for Solana, with a net profit of 4%. Although it produced mostly losing trades, winning trades had greater magnitudes than losing ones, leading this strategy to produce 2 out of the best 3 performances. It also outperformed a buy-and-hold strategy for Ethereum and Lido Staked.

Pattern 5: Inverse head and shoulders

Figure 5: *Percent Returns for Inverse Head and Shoulders and Buy-and-Hold Strategies, Grouped by Cryptocurrency*



Inverse head and shoulders appeared 1093 times and correctly predicted future price movements for 49% of trades. It performed best for Solana, earning 23%, and worst for Bitcoin, losing 3%. It was the second most common pattern and outperformed the buy-and-hold strategy for Lido Staked.

CONCLUSIONS

When comparing pattern performances, this two-month backtest attributes useful characteristics that patterns possess relative to each other. It suggests bullish pennant is the most profitable and likely to generate excess returns, (i.e. returns greater than for a buy-and-hold strategy) sloping heads and shoulders is the least common pattern on crypto price charts, and descending channel is the most likely to generate similar returns across different assets.

Aggregating data from all patterns combined also yields useful suggestions. 15.3% of all price points were involved in at least one pattern recognition; this kind of abundance suggests that patterns hold some valuable information. Since 18 out of 25 strategies tested resulted in profits, the bactest suggests that these patterns can be expected to generate positive returns when applied to crypto. However, since no pattern made correct predictions more than 50% of the time, the data also suggests that the positive returns generated may be due to a general positive trend during the backtest period. Ultimately, since only 4 out of 25 strategies generated profits in excess of a buy-and-hold strategy, the backtest's most important suggestion is that technical chart patterns alone do not comprise a profitable enough strategy to be worth implementing.

LIMITATIONS

The main limitation of this study was the relatively short span of the backtest. The backtest analyzed 136,800 historical price points, as opposed to the millions of price points that modern quantitative strategies are tested on. It was limited because the Python application programming interface used to retrieve data, yFinance, can only retrieve intraday price data (i.e. in 15 minute intervals) for the past 60 days. The short period limits how well the backtest can be expected to simulate future market conditions, and therefore limits the significance of resulting conclusions.

Another limitation lies in the chart patterns used. Patterns were chosen based on their performance on NYSE stocks, not crypto coins. Due to their differences, it is possible that different patterns would prove more profitable in each asset. This limitation suggests that other technical chart patterns could have yielded better results and implicitly suggests an area for future research: testing more than five technical chart patterns.

The conclusions of this study are limited by its focus on empirical, quantitative evidence. This paper focuses on analyzing and comparing quantitative data, without conducting statistical tests, which limits the conclusions to suggestions pending significance testing. No significance tests are conducted because there are not yet any theoretical models for cryptocurrency pricing in the literature, which would leave powerful statistical techniques without required context. For example, it has not yet been established whether prices can be modeled by random variables, therefore techniques like kernel regression are not yet applicable and the lack of theoretically expected results would leave goodness-of-fit tests without baseline.

IMPLICATIONS

The results from this paper of mixed profitability results with close to 50% accuracy for technical chart patterns aligns closely with the results of technical strategies on regular markets. The similarity hints at the implication that cryptocurrency markets hold a deeper connection to regular security markets than has previously been established. When compared to other studies for technical strategies within the crypto space, technical chart patterns generate lower returns and therefore seem to be worse than other technical strategies at predicting future price movements. The lack of definitive useability for technical chart patterns also contributes to the body of theoretical literature by implying market efficiency and introducing the possible applicability of EMH for crypto.

The most direct area of future research stemming from this study is to develop theoretical models for cryptocurrency price movements and conduct significance tests using the results achieved. Other areas include developing more complex technical algorithms to improve prediction accuracy, testing more chart patterns to establish which ones are most efficient in crypto, and increasing the data range of the backtest to improve how well it simulates future market conditions.

REFERENCES

Bessembinder, Hendrik, and Kalok Chan. “Market Efficiency and the Returns to Technical Analysis.” Financial Management, vol. 27, no. 2, 1998, pp. 5–17. JSTOR, https://doi.org/10.2307/3666289. Accessed 5 Apr. 2024.

Bessembinder, Hendrik, and Kalok Chan. "The profitability of technical trading rules in the Asian stock markets." Pacific-basin finance journal 3.2-3 (1995): 257-284.

Brown, David P., and Robert H. Jennings. “On Technical Analysis.” The Review of Financial Studies, vol. 2, no. 4, 1989, pp. 527–51. JSTOR, http://www.jstor.org/stable/2962067. Accessed 23 Apr. 2024.

Chang, Kevin, and Osler, Carol. “Methodical Madness: Technical Analysis and the Irrationality of Exchange- Rate Forecasts.” *The Economic Journal*, vol. 109, no. 458, 1999, pp. 636–61. *JSTOR*, http://www.jstor.org/stable/2565638. Accessed 23 Apr. 2024.

Chen, James. “Backtesting: Definition, How It Works, and Downsides.” Investopedia, Investopedia, www.investopedia.com/terms/b/backtesting.asp. Accessed 26 Apr. 2024.

Desagre, Christophe, Paolo Mazza, and Mikael Petitjean. "Crypto market dynamics in stressful conditions." Applied Economics 55.27 (2023): 3121-3153.

Fama, Eugene F. “Efficient Capital Markets: A Review of Theory and Empirical Work.” The Journal of Finance, vol. 25, no. 2, 1970, pp. 383–417. JSTOR, https://doi.org/10.2307/2325486. Accessed 5 Apr. 2024.

Fama, Eugene F., and Marshall E. Blume. “Filter Rules and Stock-Market Trading.” The Journal of Business, vol. 39, no. 1, 1966, pp. 226–41. JSTOR, http://www.jstor.org/stable/2351744. Accessed 5 Apr. 2024.

Felizardo, Leonardo Kanashiro, et al. "Outperforming algorithmic trading reinforcement learning systems: A supervised approach to the cryptocurrency market." Expert Systems with Applications 202 (2022): 117259.

Froot, Kenneth A., David S. Scharfstein, and Jeremy C. Stein. "Herd on the street: Informational inefficiencies in a market with short‐term speculation." The Journal of finance 47.4 (1992): 1461-1484.

Gazizova, Diana, and Katrina Agcaoili. "Technical Analysis in Cryptocurrency Market." MAJĀL: CMUQ's Undergraduate Journal 1.1 (2022).

Goutte, Stéphane, et al. "Deep learning and technical analysis in cryptocurrency market." Finance Research Letters 54 (2023): 103809.

Robert L. Hagin, and Ronald N. Kahn. “What Practitioners Need to Know about Backtesting.” Financial Analysts Journal, vol. 46, no. 4, 1990, pp. 17–20. JSTOR, http://www.jstor.org/stable/4479342. Accessed 5 Apr. 2024.

King, Willford I. “Technical Methods of Forecasting Stock Prices.” Journal of the American Statistical Association, vol. 29, no. 187, 1934, pp. 323–25. JSTOR, https://doi.org/10.2307/2278079. Accessed 5 Apr. 2024.

Levy, Robert A. “Conceptual Foundations of Technical Analysis.” Financial Analysts Journal, vol. 22, no. 4, 1966, pp. 83–89. JSTOR, http://www.jstor.org/stable/4470026. Accessed 5 Apr. 2024.

Levy, Robert A. “The Predictive Significance of Five-Point Chart Patterns.” The Journal of Business, vol. 44, no. 3, 1971, pp. 316–23. JSTOR, http://www.jstor.org/stable/2351345. Accessed 5 Apr. 2024.

Liang, Jiaqi, et al. "Towards an understanding of cryptocurrency: a comparative analysis of cryptocurrency, foreign exchange, and stock." 2019 IEEE International Conference on Intelligence and Security Informatics (ISI). IEEE, 2019.

Lo, Andrew W., and Mackinlay, Craig. “Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test.” The Review of Financial Studies, vol. 1, no. 1, 1988, pp. 41–66. JSTOR, http://www.jstor.org/stable/2962126. Accessed 5 Apr. 2024.

Lo, Andrew W., et al. “Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation.” *The Journal of Finance*, vol. 55, no. 4, 2000, pp. 1705–65. *JSTOR*, http://www.jstor.org/stable/222377. Accessed 23 Apr. 2024.

Menkhoff, Lukas, and Mark P. Taylor. “The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis.” Journal of Economic Literature, vol. 45, no. 4, 2007, pp. 936–72. JSTOR, http://www.jstor.org/stable/27646888. Accessed 5 Apr. 2024.

Joseph Mindell. “Chart Patterns.” Financial Analysts Journal, vol. 20, no. 3, 1964, pp. 66–67. JSTOR, http://www.jstor.org/stable/4469650. Accessed 5 Apr. 2024.

Nti, Isaac Kofi, Adebayo Felix Adekoya, and Benjamin Asubam Weyori. "A systematic review of fundamental and technical analysis of stock market predictions." Artificial Intelligence Review 53.4 (2020): 3007-3057.

Park, Cheol-Ho, and Scott H. Irwin. “The Profitability of Technical Analysis: A Review.” SSRN, 15 Oct. 2004, deliverypdf.ssrn.com/delivery.php?ID=389082074026093004114109110009089087049011003078061021028123003100005070112101104025033007120040011005124112000126094074100006048087029051118001085103094098077021055004000027079026116081072006082088113099029113112029029115005122123091010082031&EXT=pdf&INDEX=TRUE.

Pinches, George E. “The Random Walk Hypothesis and Technical Analysis.” Financial Analysts Journal, vol. 26, no. 2, 1970, pp. 104–10. JSTOR, http://www.jstor.org/stable/4470663. Accessed 5 Apr. 2024.

Edmund W. Tabell, and Anthony W. Tabell. “The Case for Technical Analysis.” Financial Analysts Journal, vol. 20, no. 2, 1964, pp. 67–76. JSTOR, http://www.jstor.org/stable/4469619. Accessed 5 Apr. 2024.

Treynor, Jack L., and Robert Ferguson. “In Defense of Technical Analysis.” The Journal of Finance, vol. 40, no. 3, 1985, pp. 757–73. JSTOR, https://doi.org/10.2307/2327800. Accessed 5 Apr. 2024.

Xu-Shen Zhou, and Ming Dong. “Can Fuzzy Logic Make Technical Analysis 20/20?” Financial Analysts Journal, vol. 60, no. 4, 2004, pp. 54–75. JSTOR, http://www.jstor.org/stable/4480588. Accessed 5 Apr. 2024.

APPENDICES

Appendix A: *Backtest raw data results*

The results for pattern 1 tested on Bitcoin are:

Number of times the pattern was recognized: 198

Number of times the pattern was correct: 94

for winning trades, the total percentage gain was: 28.829812682881297

for losing trades, the total percentage lost was: -22.073754093460007

The total aggregate returns for the strategy was: 6.756058589421288

Comparably, a the returns for a buy and hold strategy during the same period was:

27.919759239531

The results for pattern 1 tested on Ethereum are:

Number of times the pattern was recognized: 177

Number of times the pattern was correct: 75

for winning trades, the total percentage gain was: 25.543971427091268

for losing trades, the total percentage lost was: -28.728971151266254

The total aggregate returns for the strategy was: -3.184999724174986

Comparably, a the returns for a buy and hold strategy during the same period was:

8.032838250186325

The results for pattern 1 tested on Binance are:

Number of times the pattern was recognized: 190

Number of times the pattern was correct: 100

for winning trades, the total percentage gain was: 33.8410381816971

for losing trades, the total percentage lost was: -25.50567224006463

The total aggregate returns for the strategy was: 8.335365941632473

Comparably, a the returns for a buy and hold strategy during the same period was:

52.17684338499689

The results for pattern 1 tested on Solana are:

Number of times the pattern was recognized: 199

Number of times the pattern was correct: 92

for winning trades, the total percentage gain was: 45.82155978280325

for losing trades, the total percentage lost was: -37.398247871843566

The total aggregate returns for the strategy was: 8.42331191095968

Comparably, a the returns for a buy and hold strategy during the same period was:

50.765577556899274

The results for pattern 1 tested on Lido Staked ETH are:

Number of times the pattern was recognized: 171

Number of times the pattern was correct: 89

for winning trades, the total percentage gain was: 30.392930395944134

for losing trades, the total percentage lost was: -16.975201562490753

The total aggregate returns for the strategy was: 13.417728833453383

Comparably, a the returns for a buy and hold strategy during the same period was:

7.910411785271451

The results for pattern 2 tested on Bitcoin are:

Number of times the pattern was recognized: 63

Number of times the pattern was correct: 24

for winning trades, the total percentage gain was: 4.99317507382071

for losing trades, the total percentage lost was: -10.340051545278024

The total aggregate returns for the strategy was: -5.346876471457314

Comparably, a the returns for a buy and hold strategy during the same period was:

27.919759239531

The results for pattern 2 tested on Ethereum are:

Number of times the pattern was recognized: 56

Number of times the pattern was correct: 21

for winning trades, the total percentage gain was: 5.947813661375679

for losing trades, the total percentage lost was: -6.25724300167431

The total aggregate returns for the strategy was: -0.30942934029863156

Comparably, a the returns for a buy and hold strategy during the same period was:

8.032838250186325

The results for pattern 2 tested on Binance are:

Number of times the pattern was recognized: 53

Number of times the pattern was correct: 29

for winning trades, the total percentage gain was: 7.674662852170552 for losing trades, the total percentage lost was: -8.408641625995717

The total aggregate returns for the strategy was: -0.7339787738251641

Comparably, a the returns for a buy and hold strategy during the same period was:

52.17684338499689

The results for pattern 2 tested on Solana are:

Number of times the pattern was recognized: 50

Number of times the pattern was correct: 23

for winning trades, the total percentage gain was: 10.649517457501995

for losing trades, the total percentage lost was: -6.64592810534298

The total aggregate returns for the strategy was: 4.003589352159015

Comparably, a the returns for a buy and hold strategy during the same period was:

50.765577556899274

The results for pattern 2 tested on Lido Staked ETH are:

Number of times the pattern was recognized: 39

Number of times the pattern was correct: 23

for winning trades, the total percentage gain was: 5.010479934148048

for losing trades, the total percentage lost was: -2.890163383193228

The total aggregate returns for the strategy was: 2.1203165509548203

Comparably, a the returns for a buy and hold strategy during the same period was:

7.910411785271451

The results for pattern 3 tested on Bitcoin are:

Number of times the pattern was recognized: 77

Number of times the pattern was correct: 31

for winning trades, the total percentage gain was: 9.22667411379384

for losing trades, the total percentage lost was: -8.962367925091204

The total aggregate returns for the strategy was: 0.2643061887026357

Comparably, a the returns for a buy and hold strategy during the same period was:

27.919759239531

The results for pattern 3 tested on Ethereum are:

Number of times the pattern was recognized: 74

Number of times the pattern was correct: 31

for winning trades, the total percentage gain was: 8.83853995816434

for losing trades, the total percentage lost was: -11.32169024091929

The total aggregate returns for the strategy was: -2.4831502827549508

Comparably, a the returns for a buy and hold strategy during the same period was:

8.032838250186325

The results for pattern 3 tested on Binance are:

Number of times the pattern was recognized: 85

Number of times the pattern was correct: 38

for winning trades, the total percentage gain was: 8.30364792842537

for losing trades, the total percentage lost was: -11.917685101380453

The total aggregate returns for the strategy was: -3.614037172955083

Comparably, a the returns for a buy and hold strategy during the same period was: 52.17684338499689

The results for pattern 3 tested on Solana are:

Number of times the pattern was recognized: 85

Number of times the pattern was correct: 43

for winning trades, the total percentage gain was: 21.25437925240786

for losing trades, the total percentage lost was: -12.867645076538262

The total aggregate returns for the strategy was: 8.386734175869595

Comparably, a the returns for a buy and hold strategy during the same period was: 50.765577556899274

The results for pattern 3 tested on Lido Staked ETH are:

Number of times the pattern was recognized: 58

Number of times the pattern was correct: 28

for winning trades, the total percentage gain was: 6.51972210800264

for losing trades, the total percentage lost was: -5.658651771236298

The total aggregate returns for the strategy was: 0.8610703367663425

Comparably, a the returns for a buy and hold strategy during the same period was: 7.910411785271451

The results for pattern 4 tested on Bitcoin are:

Number of times the pattern was recognized: 314

Number of times the pattern was correct: 146

for winning trades, the total percentage gain was: 46.002279790463554

for losing trades, the total percentage lost was: -37.73899986919037

The total aggregate returns for the strategy was: 8.263279921273176

Comparably, a the returns for a buy and hold strategy during the same period was:

27.919759239531

The results for pattern 4 tested on Ethereum are:

Number of times the pattern was recognized: 296

Number of times the pattern was correct: 144

for winning trades, the total percentage gain was: 60.564983301071585

for losing trades, the total percentage lost was: -36.919501479229375

The total aggregate returns for the strategy was: 23.645481821842214

Comparably, a the returns for a buy and hold strategy during the same period was:

8.032838250186325

The results for pattern 4 tested on Binance are:

Number of times the pattern was recognized: 319

Number of times the pattern was correct: 172

for winning trades, the total percentage gain was: 58.94377874886132

for losing trades, the total percentage lost was: -40.15528240905174

The total aggregate returns for the strategy was: 18.788496339809573

Comparably, a the returns for a buy and hold strategy during the same period was:

52.17684338499689

The results for pattern 4 tested on Solana are:

Number of times the pattern was recognized: 315

Number of times the pattern was correct: 158

for winning trades, the total percentage gain was: 72.99830232881722

for losing trades, the total percentage lost was: -68.19090241306432

The total aggregate returns for the strategy was: 4.807399915752897

Comparably, a the returns for a buy and hold strategy during the same period was:

50.765577556899274

The results for pattern 4 tested on Lido Staked ETH are:

Number of times the pattern was recognized: 273

Number of times the pattern was correct: 130

for winning trades, the total percentage gain was: 42.85637223960364

for losing trades, the total percentage lost was: -31.055595499641285

The total aggregate returns for the strategy was: 11.800776739962348

Comparably, a the returns for a buy and hold strategy during the same period was:

7.910411785271451

The results for pattern 5 tested on Bitcoin are:

Number of times the pattern was recognized: 224

Number of times the pattern was correct: 94

for winning trades, the total percentage gain was: 23.46060993134884

for losing trades, the total percentage lost was: -26.45172624748201

The total aggregate returns for the strategy was: -2.991116316133169

Comparably, a the returns for a buy and hold strategy during the same period was: 27.919759239531

The results for pattern 5 tested on Ethereum are:

Number of times the pattern was recognized: 208

Number of times the pattern was correct: 101

for winning trades, the total percentage gain was: 27.862350601752002

for losing trades, the total percentage lost was: -22.614800364387094

The total aggregate returns for the strategy was: 5.247550237364907

Comparably, a the returns for a buy and hold strategy during the same period was: 8.032838250186325

The results for pattern 5 tested on Binance are:

Number of times the pattern was recognized: 195

Number of times the pattern was correct: 90

for winning trades, the total percentage gain was: 32.99247350441446

for losing trades, the total percentage lost was: -26.069184214785356

The total aggregate returns for the strategy was: 6.923289289629109

Comparably, a the returns for a buy and hold strategy during the same period was:

52.17684338499689

The results for pattern 5 tested on Solana are:

Number of times the pattern was recognized: 222

Number of times the pattern was correct: 119

for winning trades, the total percentage gain was: 67.07560681752305

for losing trades, the total percentage lost was: -44.54060072652338

The total aggregate returns for the strategy was: 22.535006090999676

Comparably, a the returns for a buy and hold strategy during the same period was:

50.765577556899274

The results for pattern 5 tested on Lido Staked ETH are:

Number of times the pattern was recognized: 244

Number of times the pattern was correct: 132

for winning trades, the total percentage gain was: 34.641320104111855

for losing trades, the total percentage lost was: -20.41888798771957

The total aggregate returns for the strategy was: 14.222432116392284

Comparably, a the returns for a buy and hold strategy during the same period was:

7.910411785271451

Appendix B: *Python program used to conduct backtest*

```python
# raw packages
import pandas as pd
import numpy as np

# Data Source

import yfinance as yf

# Data Visualization

import finplot as fplt


Bitcoin = yf.Ticker("BTC-USD")
Ethereum = yf.Ticker("ETH-USD")
Binance = yf.Ticker("BNB-USD")
Solana = yf.Ticker("SOL-USD")
Lido = yf.Ticker("STETH-USD")

def priceChart(priceHistory):

    fplt.candlestick_ochl(priceHistory[['Open','Close','High','Low']])
    fplt.show()

    return 0


def main():

    #prints Bitcoin, Ethereum, and Binance price history data for january and february

    btcHist = Bitcoin.history(start = '2024-02-24', end='2024-04-21', interval='15m')
    ethHist = Ethereum.history(start = '2024-02-24', end='2024-04-21', interval='15m')
    bnbHist = Binance.history(start = '2024-02-24', end='2024-04-21', interval='15m')
    solHist = Solana.history(start = '2024-02-24', end='2024-04-21', interval='15m')
    lidHist = Lido.history(start='2024-02-24', end='2024-04-21', interval='15m')
```

```python
    for i in range(1,6):
        TestPattern1(btcHist.iloc[:,0].tolist(), "Bitcoin", i)
        TestPattern1(ethHist.iloc[:,0].tolist(), "Ethereum", i)
        TestPattern1(bnbHist.iloc[:,0].tolist(), "Binance", i)
        TestPattern1(solHist.iloc[:,0].tolist(), "Solana", i)
        TestPattern1(lidHist.iloc[:,0].tolist(), "Lido Staked", i)


    return 0


def TestPattern1(pricesList, crypto, patternNumber):
    patternRec = 0 # number of times pattern appeared
    patternCor = 0 #number of times pattern worked

    percentGains = [] #list of the percent gains to be made from winning trades
    percentLosses = [] #list of the percent losses to be made from losing trades



    for i in range(6, len(pricesList)): #Counts how many times pattern appeared / worked across 2 months
          if patternNumber == 1:
                condition = pricesList[i-1] < pricesList[i-3] < pricesList[i-2] < pricesList[i-5] > pricesList[i-4]
          elif patternNumber == 2:
                condition = pricesList[i-1] < pricesList[i-3] < pricesList[i-5] < pricesList[i-2] > pricesList[i-4]
          elif patternNumber == 3:
                condition = pricesList[i-1] < pricesList[i-5] < pricesList[i-3] < pricesList[i-2] > pricesList[i-4]
          elif patternNumber == 4:
                condition = pricesList[i-1] < pricesList[i-3] < pricesList[i-5] < pricesList[i-4] > pricesList[i-2]
          elif patternNumber == 5:
                condition = pricesList[i-1] < pricesList[i-5] < pricesList[i-3] < pricesList[i-4] > pricesList[i-2]
          if condition:
               patternRec += 1
               if pricesList[i] < pricesList[i-1]:
                     patternCor += 1
                     percentGains.append((pricesList[i-1] - pricesList[i])/pricesList[i])
               else:
```

```python
                percentLosses.append((pricesList[i-1] - pricesList[i]) / pricesList[i])


    sum = 0
    for i in range(len(percentGains)):
        sum += percentGains[i]

    sumLoss = 0
    for i in range(len(percentLosses)):
        sumLoss += percentLosses[i]

    print(f"The results for pattern {patternNumber} tested on {crypto} are:")
    documentResults(patternRec, patternCor, sum, sumLoss, (pricesList[len(pricesList) - 1] - pricesList[0]) / pricesList[0])
    return 0


def documentResults(patternRec, patternCor, sumGains, sumLoss, bhReturns):
    print(f"Number of times the pattern was recognized: {patternRec}")
    print(f"Number of times the pattern was correct: {patternCor}")
    print(f"for winning trades, the total percentage gain was: {sumGains * 100}")
    print(f"for losing trades, the total percentage lost was: {sumLoss * 100}")
    print(f"The total aggregate returns for the strategy was: {(sumGains + sumLoss) * 100}")
    print(f"Comparably, a the returns for a buy and hold strategy during the same period was: {bhReturns * 100}")
    print()



if __name__ == "__main__":
    main()
```