Crypto Price Simulation Strategies

ISYE 6644 Simulation
Final Report
Group 21

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I. ABSTRACT

The goal of this research is to investigate trading methods for cryptocurrencies that are tailored to the market's volatility. We devised a plan that used Monte Carlo simulations, Hidden Markov Models (HMM), and historical pricing data. Using a Moving Average Crossover Strategy, we examined the results of our approach on six popular cryptocurrencies: Dogecoin, Pepe, Shiba Inu, Dogwifhat, Ethereum, Bitcoin, and Pepe. In order to make the strategy more realistic, we also included past news occurrences. We then evaluated the approach's performance using important metrics including ROI, Sharpe Ratio, and Maximum Drawdown. Our research reveals that different cryptocurrencies have different risk-return profiles, underscoring the significance of flexible methods that are adjusted according to market situations. This study provides insightful information for creating winning trading plans in the ever-changing bitcoin market.

II. BACKGROUND

The popularity of cryptocurrencies has recently surged due to their remarkable price fluctuations and substantial profit possibilities. We started a project to create and test our own cryptocurrency trading method in order to dive into this vibrant and quickly changing market (Gandal & Halaburda, 2016; Corbet, Lucey, & Yarovaya, 2019). Using Jupyter Notebook, we could see how our plan performed through charts and data(Yahoo Finance, n.d.). Our objective in this research paper is to develop a system that could successfully negotiate the erratic cryptocurrency markets and the goal is to yield substantial profits(Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2017).

II. PROBLEM DEFINITION

The cryptocurrency market's high volatility and unpredictability make it challenging for traders to achieve consistent profits, as traditional models often fall short(Chan, Chu, Nadarajah, & Osterrieder, 2017)(Kim et al., 2016). To handle price fluctuations, recognize and react to market trends quickly, and take into account outside variables like news about regulations and technology improvements, we require a strong trading strategy. Our goal is to create a trading strategy that is both realistic and flexible by incorporating historical news data, utilizing Hidden Markov Models (HMM) to forecast market patterns, and use Monte Carlo simulations to calculate risk and return. Visualizing historical data, trading signals, and portfolio performance will allow us to evaluate the strategy's effectiveness and profitability (Liu & Tsyvinski, 2018).

III. DATA COLLECTION AND PREPROCESSING

We analyzed the historical price data of six cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Dogecoin (DOGE), Pepe (PEPE), Shiba Inu (SHIB), and Dogwifhat (WIF). We downloaded this data from Yahoo Finance. To get it ready for analysis, we first converted the 'Date' column to a datetime format, sorted everything in chronological order, and removed any rows with missing values. This ensured our data was clean and reliable for our study. To guarantee correctness and consistency, this function was then applied to each cryptocurrency dataframe.

IV. IMPLEMENTATION OF MOVING AVERAGE CROSSOVER STRATEGY

To test the first strategy's efficacy in trading different cryptocurrencies, we first applied a Moving Average Crossover Strategy. Based on the crossing points of these moving averages, the approach generated buy and sell signals using both short-term (20-day) and long-term (50-day) simple moving averages (SMA). A purchase signal was formed when the short-term moving average crossed above the long-term moving average, and a sell signal was generated when it passed below it. $100,000 was first invested in the trading simulation. We kept an eye on the portfolio value of each cryptocurrency over time and responded to the signals generated by the indicators by making transactions. The portfolio value was calculated by adjusting the initial capital based on the cumulative daily returns of the positions held.

For each of the six cryptocurrencies, we plotted graphs illustrating the portfolio value over time and the moving averages with trading signals to showcase the cumulative effects of the Moving Average Crossover Strategy. As an example, the "BTC Portfolio Value Over Time" (Figure 1) graph demonstrates the growth and drawdown periods, while the "BTC Moving Averages and Trading Signals" graph highlights the buy and sell signals that drive these changes, reflecting the strategy's profit potential and risks.

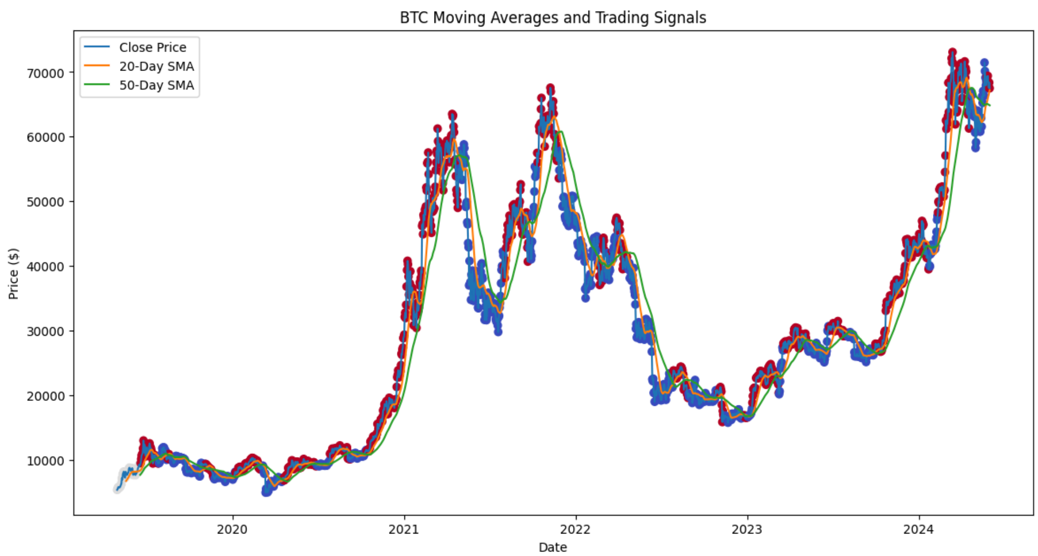

Figure 1: BTC Moving Averages and Trading Signals

Performance Evaluation

We computed three critical measures in order to evaluate the strategy's effectiveness.The six cryptocurrencies were tested using a sharpe ratio, maximum drawdown, and return on investment (ROI). ROI measures the overall profitability of the approach as a percentage of the beginning money. The Sharpe Ratio evaluates the risk-adjusted return by comparing the average daily return to the daily return standard deviation; a higher ratio indicates better risk-adjusted performance. The largest percentage fall in portfolio value from peak to trough indicates the degree of risk exposure.

The results showed that the six cryptocurrencies that were looked at performed differently. With a ROI of 2.826, the greatest Sharpe Ratio of 0.1912, and the lowest Maximum Drawdown of -20.03%, WIF was the asset that performed the best. This suggests that WIF achieved strong returns with favorable risk-adjusted performance and minimal risk exposure. As opposed to this, DOGE had the highest return on investment (8.841) but also the highest volatility (-109.15% maximum drawdown) and the lowest Sharpe Ratio (0.0505). As demonstrated in Figure 2, PEPE also had a high ROI of 5.472 and a respectably good Sharpe Ratio of 0.1203, but it also had a significant risk with a Maximum Drawdown of -173.34%.

These findings highlight the diverse risk and return profiles of the analyzed cryptocurrencies. While WIF presented a balanced profile with strong returns and minimal risk, DOGE and PEPE offered higher returns at the cost of increased volatility and risk.This analysis emphasizes how crucial it is to take into account risk and return metrics when assessing how well bitcoin investments have performed.

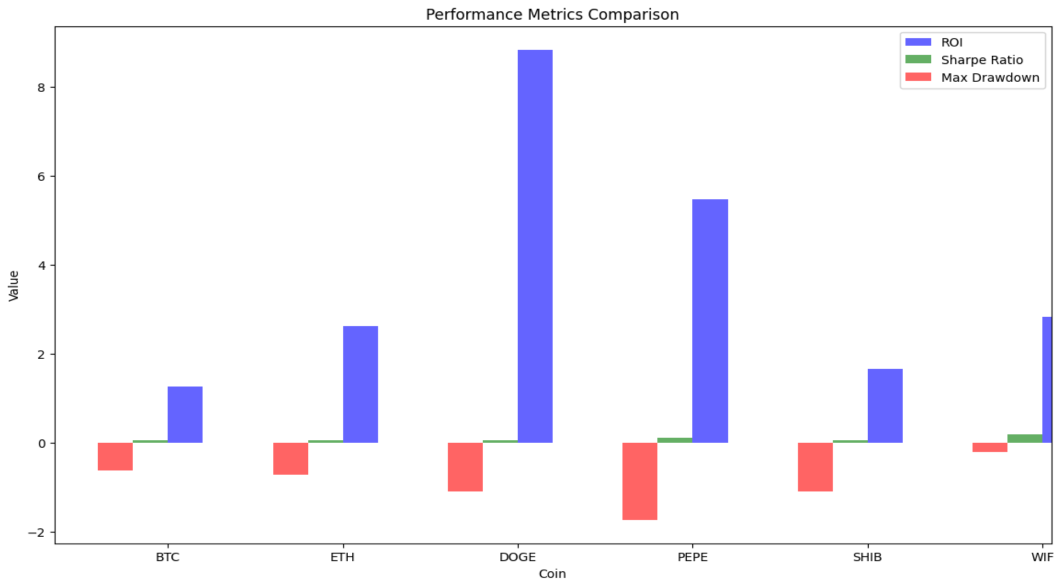

Figure 2: Performance Metrics of Moving Average Crossover Strategy for Six Cryptocurrencies

V. INCORPORATION OF NEWS EVENTS

We included important news stories that might have an impact on the values of the cryptocurrencies we selected in order to make our simulation more realistic (Munim et al., 2019; Urquhart et al., 2018; EarnPark, 2022). We collected historical news data from sources such as Google News or CryptoPanic. We analyzed the effect of some major events happening in Bitcoin prices, from the year of 2019 to 2024. Several major events, including the Binance hack on May 7, 2019, had resulted in a negative impact due to the theft of 7,000 BTC that was worth $40.7 million, and the PayPal announcement on October 21, 2020, that positively influenced the market by supporting cryptocurrency transactions. On the other hand, positive events, such as Bitcoin exceeding $40,000 for the first time on January 8, 2021, and the launch of Bitcoin ETFs in the U.S. on January 1, 2024, collectively contributed to significant market uptakes. Some other events like the market crash on March 12, 2020 due to COVID-19, and the collapse of the FTX exchange on November 8, 2022, also had collectively negative impacts, causing substantial price drops, which is shown in Figure 3 below.

	Date	Event Description	Impact
0	2019-05-07	Binance Hack: 7,000 BTC stolen worth $40.7 million	negative
1	2019-09-23	Bakkt Launches Bitcoin Futures Contracts	positive
2	2020-03-12	Crypto Market Crash: Bitcoin drops 50% due to COVID-19	negative
3	2020-10-21	PayPal Announces Support for Cryptocurrency Transactions	positive
4	2021-01-08	Bitcoin Surpasses $40,000 for the First Time	positive
5	2021-05-12	Tesla Stops Accepting Bitcoin Payments	negative
6	2022-03-15	Regulatory Announcement on Crypto Taxation in the U.S.	negative
7	2022-09-15	Ethereum Merge: Transition from Proof of Work to Proof of Stake	positive
8	2022-11-08	FTX Exchange Collapse	negative
9	2023-06-01	Bitcoin ETFs Approved in Several Regions	positive
10	2023-12-10	Rise of DeFi and NFTs: Major projects gain traction	positive
11	2024-01-01	First Bitcoin ETF Launched in the U.S.	positive
12	2024-04-15	Blockchain Life 2024: Major Event in Dubai	positive
13	2024-05-29	Consensus 2024: Major Crypto Conference in Austin, Texas	positive

Figure 3: Impact of Major News Events on Bitcoin Prices (2019-2024)

The analysis's findings demonstrate the effects of major news events on variations in BTC and ETH prices across intervals of one day, three days, five days, seven days, and ten days. Positive developments for Bitcoin caused price gains throughout the course of ten days. The average price change was +7.43% after one day, +0.42%, three days, +1.23%, five days, +5.12%, seven days, and ten days. This implies that positive news reports benefit Bitcoin values over the long term, since the market absorbs the information and prices often rise. In contrast, negative events for BTC caused immediate and significant price drops. As seen in Figure 4, the average price change was -11.98% after one day, -12.93% after three days, -12.23% after five days, -16.90% after seven days, and -17.07% after ten days. These showed that bad news stories have a significantly negative influence on Bitcoin values, which gets worse over time.

BTC Average Price Change After News Events

Event Impact	1 Days	3 Days	5 Days	7 Days	10 Days
Positive	0.42%	1.23%	1.47%	5.12%	7.43%
Negative	-11.98%	-12.93%	-12.23%	-16.90%	-17.07%

Figure 4: BTC Average Price Change After News Events

ETH Average Price Change After News Events

Event Impact	1 Days	3 Days	5 Days	7 Days	10 Days
Positive	-1.02%	-1.35%	0.29%	6.88%	12.06%
Negative	-13.42%	-12.17%	-10.38%	-14.37%	-10.60%

Figure 5: ETH Average Price Change After News Events

The impact research of ETH (Ethereum) reveals that, potentially as a result of market adjustments or profit-taking, positive news events initially had a somewhat negative influence on prices in the near term, with an average price change of -1.02% after one day and -1.35% after three. But starting on day five, the effect started to show signs of improvement, with average price changes of +0.29% after 5 days, +6.88% after 7 days, and +12.06% after 10 days. This indicates that positive news has a delayed but strong positive effect on ETH prices. For negative events, ETH experienced immediate and significant negative impacts on prices, similar to BTC. The average price change was -13.42% after 1 day, -12.17% after 3 days, -10.38% after 5 days, -14.37% after 7 days, and -10.60% after 10 days as shown in Figure 5. The magnitude of the decline slightly reduced over time, suggesting that while negative news leads to immediate price drops, the market starts to stabilize after a week.

In summary, both BTC and ETH benefit from positive news events, but the effect is more pronounced and quicker for BTC, while ETH sees a delayed positive impact. Following bad news, the prices of both cryptocurrencies drop sharply and instantly; BTC's decrease gets worse over time, while ETH's decline starts to stabilize after a week.

VI. HIDDEN MARKOV MODELS (HMM)

We will use Hidden Markov Models (HMM)(Cappe, Moulines, & Rydén, 2005)(Rabiner, 1989)(Fishman, 2013)(Glasserman, 2004) to simulate the basic market circumstances, including bull, bear, and stagnant markets. We started by defining the market states and initializing the HMM with appropriate parameters. Then, we trained the model using historical price data to capture transitions between different market states. Once trained, we used the HMM to predict the current market state based on observed price data. Based on these predictions, we adjusted our trading strategy, potentially increasing or decreasing position sizes according to the market state.

Mathematics Behind Hidden Markov Models

A statistical model known as the Hidden Markov Model is used to explain how a system changes over time from one state to another, each of which is connected to a probability distribution (Cappe, Moulines, 2005; Rabiner, 1989). The system's states are concealed, yet every state has an output that can be seen. The core components of an HMM include:

- **Initial State Probabilities (π):** The probability of starting in each state.
- **State Transition Probabilities (A):** The probability of transitioning from one state to

another.

- **Emission Probabilities (B):** The probability of observing a particular output from a state.

Mathematically, the HMM is defined by:

- $\pi = \{\pi_i\}$ where π_i is the probability of starting in state i.
- $A=\{a_{ij}\}$ where a_{ij} is the probability of transitioning from state i to state j.
- $B=\{b_j(o_t)\}$ where $b_j(o_t)$ is the probability of observing ot given the state j.

Expectation-Maximization Algorithm (EM)

The HMM's parameters are estimated using the EM technique. There are two primary steps in it:

1. **Expectation Step (E-step):** Using the most recent estimates of the parameters, determine the expected values of the hidden variables.
2. **Step of Maximization (M-step):** Using the predicted values determined in the E-step as a guide, adjust the parameters to maximize the likelihood function.

Viterbi Algorithm

Given the observable sequence, the most likely sequence of hidden states is found using the Viterbi method.

1. Log Gaussian Probability:

$$\log\_gaussian\_prob(x,\mu,\sigma^2) = -0.5(\log(2\pi\sigma^2) + \frac{(x-\mu)^2}{\sigma^2}$$

2. Forward Algorithm (α):

$$\alpha_t\,(i) = (\sum_{j=1}^{N} \alpha_{t-1}(j)\cdot\ \alpha_{ji}\ )\ \cdot\ b_i(o_t)$$

3. Backward Algorithm (β):

$$\beta_t(i) = \sum_{j=1}^{N} \beta_{t+1}(j)\cdot\ \alpha_{ij}\ \cdot\ b_j(o_{t+1})$$

4. Gamma (γ):

$$\gamma_t(i) = \frac{\alpha_t(i) \cdot \beta_t(i)}{\sum_{j=1}^{N} \alpha_t(j) \cdot \beta_t(i)}$$

5. Xi (ξ):

$$\xi_t(i,j) = \frac{\alpha_t(i) \cdot \alpha_{ij} \cdot b_j(o_{t+1}) \cdot \beta_{t+1}(j)}{\sum_{k=1}^{N} \sum_{l=1}^{N} \alpha_t(k) \cdot \alpha_{kl} \cdot b_l(o_{t+1}) \cdot \beta_{t+1}(l)}$$

Incorporating Hidden Markov Models

We applied Hidden Markov Models (HMMs) to six cryptocurrencies. The methodology involved calculating log returns from the closing prices and fitting an HMM with three hidden states to each cryptocurrency's log return series. These hidden states were interpreted as follows: State 0 represented a Bull Market with increasing prices, State 1 a Bear Market with decreasing prices, and State 2 a Stagnant Market with fluctuating prices without a clear trend as shown in Figure 6. To determine these states, we utilized the Expectation-Maximization (EM) algorithm for parameter estimation and the Viterbi algorithm for state sequence inference.

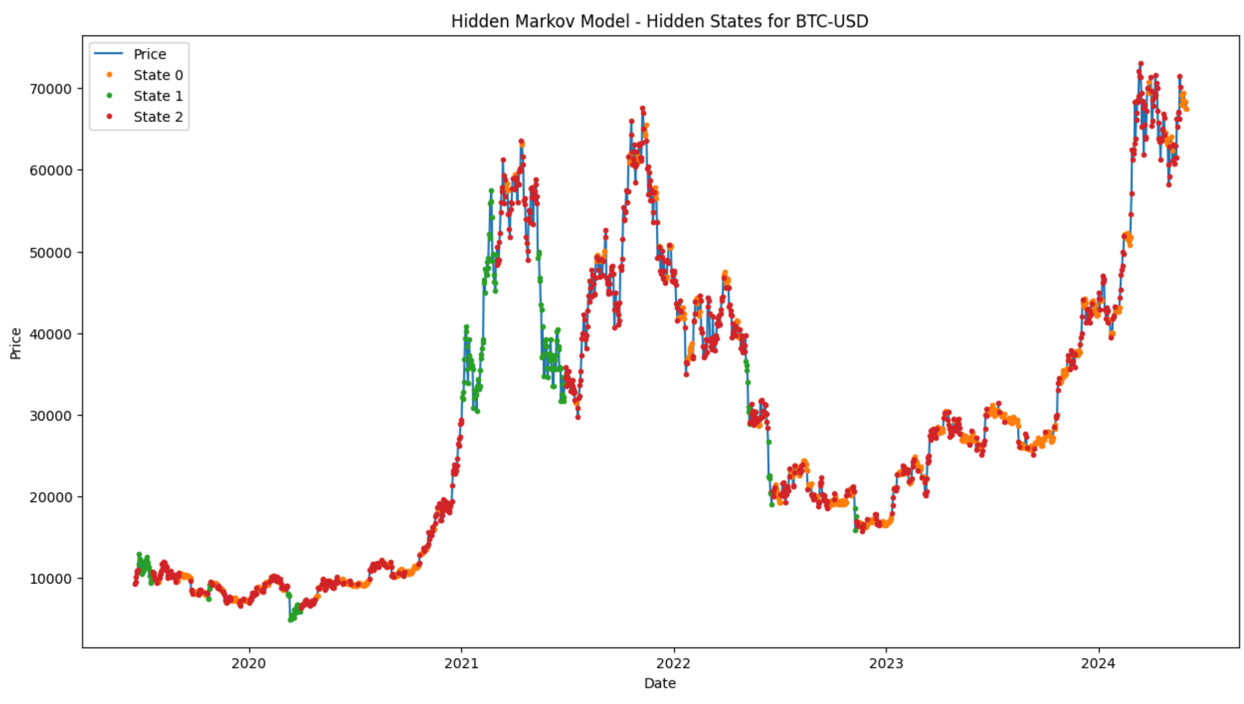

Figure 6: Hidden Markov Model - Hidden States for BTC-USD

The results indicated distinct market states for each cryptocurrency. BTC and DOGE were predominantly in a Bull Market, suggesting strategies that involved increasing position sizes or holding longer. In contrast, ETH, PEPE, and WIF were predominantly in a Stagnant Market, recommending maintaining neutral positions or reducing trading frequency. SHIB was primarily in a Bear Market, suggesting a decrease in position size or quick exits. To evaluate the effectiveness of these strategies, we simulated trading with initial capital of $100,000 for each cryptocurrency, and adjusting portfolio positions according to the inferred states. Performance metrics, including Return on Investment (ROI), Sharpe Ratio, and Maximum Drawdown, were calculated for each cryptocurrency.

The performance metrics for the analyzed cryptocurrencies revealed notable differences in returns and risk profiles. With the highest Sharpe Ratio of 0.1691, the lowest Maximum Drawdown of -28.54%, the highest ROI of 1.8805 (188.05% return), and the best performance, WIF stood out. These metrics indicate substantial gains with low risk. The most volatile investment, DOGE, had the highest ROI of 21.3108 (2131.08% return), but it also had the largest Maximum Drawdown of -49.21% and the lowest Sharpe Ratio of 0.0607. PEPE showed an ROI of 149.6782, a Sharpe Ratio of 0.1321, and a Maximum Drawdown of -81.93%, indicating high returns with considerable risk. BTC and ETH had moderate returns with ROIs of 3.6520 and 9.3744, and Sharpe Ratios of 0.0459 and 0.0577, but both experienced substantial Maximum Drawdowns around -70%. SHIB had the lowest ROI of 0.0493 and a Sharpe Ratio of 0.0139, with a Maximum Drawdown of -66.64%, indicating poor performance in both returns and risk. From the result, WIF offered the best balance of strong returns and minimal risk, while DOGE and PEPE provided high returns with greater volatility.

VII. MONTE CARLO INTEGRATION

By creating random variables and observing the results, Monte Carlo simulations, a potent tool with roots in probability and statistical sampling, are used to describe and forecast the behavior of complex systems. In financial modeling, these simulations forecast future price paths of assets by generating numerous possible scenarios. The key mathematical steps involved in this process include random variable generation, the Box-Muller transform, price path generation, and the estimation of expected return and risk. Using these mathematical procedures, Monte Carlo simulations offer a stable and adaptable framework for simulating the volatility and uncertainty present in financial markets. These simulations provide insightful information about the possible future performance of assets by producing a broad range of possible outcomes. This enables investors to make well-informed decisions based on probabilistic forecasts rather than deterministic predictions.

Mathematics Behind Hidden Markov Models

The simulation process begins with the generation of random variables that follow a specific probability distribution. For financial models, these variables typically represent daily returns of an asset, assumed to follow a normal distribution based on the Central Limit Theorem. The Box-Muller transform is commonly used to generate these normally distributed random variables. This mathematical algorithm converts two independent, uniformly distributed random numbers into two independent, normally distributed random numbers using the equations (Fishman, 2013; Glasserman, 2004):

$$Z_0 = \sqrt{-\ 2lnU_1cos(2\pi U_2)}$$

$$Z_1 = \sqrt{-\ 2lnU_1sin(2\pi U_2)}$$

- where U_1 and U_2 are independent random variables uniformly distributed in the interval (0, 1),
- Z_0 and Z_1 are independent standard normally distributed random variables.

Using these generated random daily returns, future price paths are simulated iteratively for a specified number of days, starting from the last known price. The price at each subsequent day is calculated using:

$$P = P_t \times (1 + r_{t+1})$$

- where P_t is the price at day t
- r_{t+1} is the randomly generated return for day $t + 1$.

Incorporating Monte Carlo Simulation

To effectively communicate the results, we created two primary visualizations for each coin. The first visualization, "Actual vs. Simulated Price Paths," plotted historical price data alongside a subset of the simulated price paths. This comparison illustrates the alignment between actual historical prices and the range of possible future scenarios generated by the simulations as shown in Figure 7. The second visualization, a "Histogram of Final Prices," was generated to highlight the distribution of potential future prices. The histogram also indicated the median final price, offering insight into the central tendency of the simulated outcomes as shown in Figure 8.

Making more educated financial decisions is made easier with the aid of these visualizations, which provide insight into the possible range of future prices, the probability of certain outcomes, and the accompanying dangers. For instance, in the instance of Bitcoin (BTC), these graphs clearly illustrated the dangers and potential profits of the Moving Average Crossover Strategy. They also successfully illustrated the strategy's cumulative impacts.

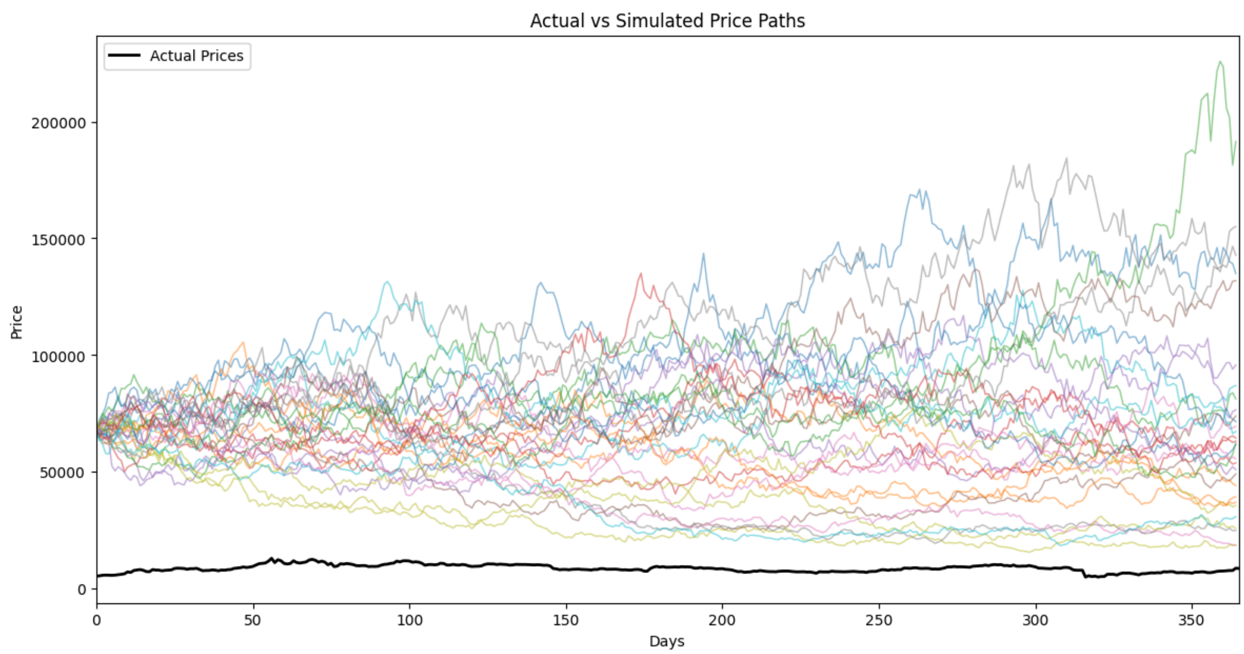

Figure 7: Actual vs Simulated Price Paths

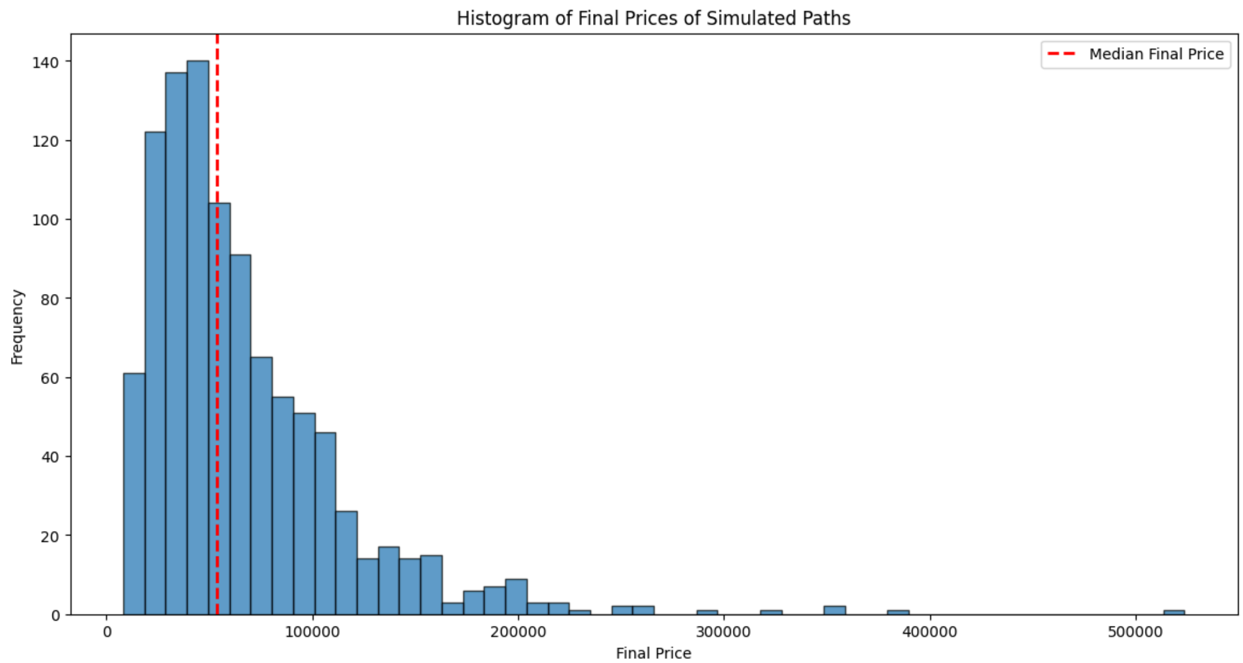

Figure 8: Histogram of Final Prices of Simulated Paths

From our simulation, Bitcoin (BTC) exhibited a final price of $52,048.16, with an expected return of -0.000069 and very low risk (standard deviation of 0.001821), indicating stability but limited growth potential. Ethereum (ETH) showed a final price of $2,592.23, an expected return of 0.000051, and low risk (standard deviation of 0.002204), suggesting moderate growth with minimal volatility.

Dogecoin (DOGE) demonstrated a final price of $0.020192, a positive expected return of 0.000055, and moderate risk (standard deviation of 0.005418), indicating potential for higher returns with higher volatility. In contrast, PEPE showed a final price of $0.000002, a negative expected return of -0.000267, and high risk (standard deviation of 0.014067), indicating poor performance and significant volatility. Shiba Inu (SHIB) had a final price of $0.000000, a positive expected return of 0.000101, and relatively high risk (standard deviation of 0.007972), indicating potential for growth but with notable volatility. WIF exhibited a final price of $0.015562, a negative expected return of -0.000561, and moderate risk (standard deviation of 0.008815), indicating poor performance and considerable volatility.

Comparative Performance Analysis

On the other hand, Ethereum (ETH) turned out to be the top performer in terms of risk adjusted returns. Because of its low risk and slightly positive expected return, it is a great option for investors looking for steady growth without risk. Compared to other cryptocurrencies, Dogecoin (DOGE) and Shiba Inu (SHIB) were more volatile, but this only attracted investors who were able to take on greater risk in exchange for a higher potential return. For risk-averse investors who prioritize stability over potential return, Bitcoin (BTC) is a suitable choice as it has very little expected growth and continues to be a steady asset with very low risk. On the other hand, PEPE and WIF, which had negative expected returns and significant risks, indicated poor performance and high volatility, lowering their possibility to be investment opportunities.

Statistical Analysis and Insights

A statistical study was done to find out how significant the returns variations amongst the cryptocurrencies were. Significant variations in returns were observed among multiple cryptocurrency pairs, as demonstrated by the p-values (p-value < 0.05). Notably, notable distinctions were discovered between BTC and WIF, BTC and SHIB, BTC and PEPE, and BTC and ETH. Additionally, ETH showed significant differences compared to PEPE and WIF. DOGE exhibited significant differences in returns compared to PEPE and WIF. Finally, significant differences were observed between PEPE and SHIB, as well as SHIB and WIF.

On the other hand, no appreciable variations in profits were discovered for the pairs PEPE vs. WIF, ETH vs. DOGE, ETH vs. SHIB, DOGE vs. SHIB, and BTC vs. DOGE (p-value > 0.05). various results offer insightful information on how various cryptocurrencies perform in comparison.BTC underperforms compared to ETH and SHIB but outperforms PEPE and WIF. When compared to BTC, ETH, and SHIB, DOGE performs better than PEPE and WIF, but not significantly better than ETH. In comparison to BTC, ETH, DOGE, and SHIB, PEPE performs worse.

SHIB outperforms PEPE and WIF but shows no significant difference compared to ETH and DOGE. WIF underperforms compared to BTC, ETH, DOGE, and SHIB as shown in Figure 9.

	Coin 1	Coin 2	T-Statistic	P-Value
0	BTC	ETH	-5.365970	8.144253e-08
1	BTC	DOGE	-1.063948	2.873733e-01
2	BTC	PEPE	2.109930	3.488832e-02
3	BTC	SHIB	-2.761732	5.759056e-03
4	BTC	WIF	5.202447	2.002723e-07
5	ETH	DOGE	1.607601	1.079464e-01
6	ETH	PEPE	3.176889	1.492957e-03
7	ETH	SHIB	-0.873041	3.826591e-01
8	ETH	WIF	6.831244	8.853572e-12
9	DOGE	PEPE	2.387993	1.695506e-02
10	DOGE	SHIB	-1.722170	8.505645e-02
11	DOGE	WIF	5.127763	2.965366e-07
12	PEPE	SHIB	-3.245397	1.175315e-03
13	PEPE	WIF	1.030545	3.027691e-01
14	SHIB	WIF	5.846160	5.109672e-09

Figure 9: Statistical Significance of Differences in Cryptocurrency Returns

Final Portfolio Values

Assuming an initial investment of 100,000 units in each cryptocurrency, the final portfolio values, as derived from the Monte Carlo simulations, reveal substantial differences in potential outcomes. BTC yielded a final portfolio value of 5,204,816,426.87 units, reflecting its strong performance in the simulation. ETH resulted in 259,223,062.49 units, showcasing its robust growth potential. DOGE, with a final value of 2,019.21 units, demonstrated moderate performance, while PEPE resulted in a significantly lower value of 0.25 units, indicating poor performance. SHIB ended with 0.02 units, reflecting high volatility and risk, and WIF concluded with 1,556.20 units, indicating underperformance compared to other cryptocurrencies.

These final portfolio values illustrate the significant differences in simulated performance based on an initial investment. The findings emphasize how different cryptocurrencies can have different outcomes, which emphasizes how crucial it is to comprehend each one's particular risk and return characteristics before making an investment.

VIII. VOLUME ANALYSIS

The volume analysis explored correlation between trading volume and price reversals in major cryptocurrencies. By evaluating the closing prices and trading volumes of BTC, ETH, DOGE, PEPE, SHIB, and WIF, we investigated whether volume could act as a predictive indicator for price fluctuations.

We started by identifying reversal dates for each cryptocurrency, which are points where the price changes direction. This was done by detecting local maxima and minima in the closing prices. We then calculated the number of days between the reversal dates of BTC/ETH and those of the memecoins (DOGE, PEPE, SHIB, WIF). For each reversal date in each set, we found the nearest reversal date in the other set, and computed the difference in days across all pairs (BTC-DOGE, BTC-PEPE, BTC-SHIB, BTC-WIF, ETH-DOGE, ETH-PEPE, ETH-SHIB, ETH-WIF).

	Mean Difference in Days
BTC-DOGE	-0.18
BTC-PEPE	572.25
BTC-SHIB	142.55
BTC-WIF	767.06
ETH-DOGE	-0.17
ETH-PEPE	580.89
ETH-SHIB	150.55
ETH-WIF	777.09

Figure 10:Differences in Reversal Dates Between Major Cryptocurrencies and Memecoins

The variability in timing differences for pairs involving PEPE, SHIB, and WIF indicated that reversals in BTC or ETH sometimes precede and sometimes follow those in the memecoins. This suggests there is no consistent lead-lag pattern between major cryptocurrencies and memecoins. DOGE, the more established memecoin, displayed smaller mean differences, reflecting more predictable timing differences with BTC and ETH, as shown in Figure 10.

The box plots illustrate the distribution of timing differences between reversals in BTC/ETH and various memecoins (DOGE, PEPE, SHIB, WIF). For BTC, the BTC-DOGE pair shows a tight distribution with a small interquartile range, indicating consistent and predictable timing differences. In contrast, BTC-PEPE displays a wider distribution, suggesting that PEPE responds more slowly and less predictably to changes in BTC. Similarly, BTC-SHIB shows moderate variability, indicating some consistency but less predictability than DOGE. BTC-WIF, like PEPE, has a wide distribution with high variability, reflecting slow and unpredictable responses to BTC changes.

A similar pattern is observed for ETH. The ETH-DOGE pair shows a tight distribution, indicating quick and predictable responses to ETH changes. Conversely, ETH-PEPE has a wide distribution, highlighting high variability and slower response times to ETH changes. ETH-SHIB exhibits moderate variability, indicating some consistency but less predictability compared to DOGE. ETH-WIF, similar to PEPE, shows high variability and slower responses to ETH changes. These observations emphasize that newer memecoins like PEPE and WIF tend to have slower and less predictable reversal timings in relation to both BTC and ETH compared to more established memecoins like DOGE, as shown in Figure 11.

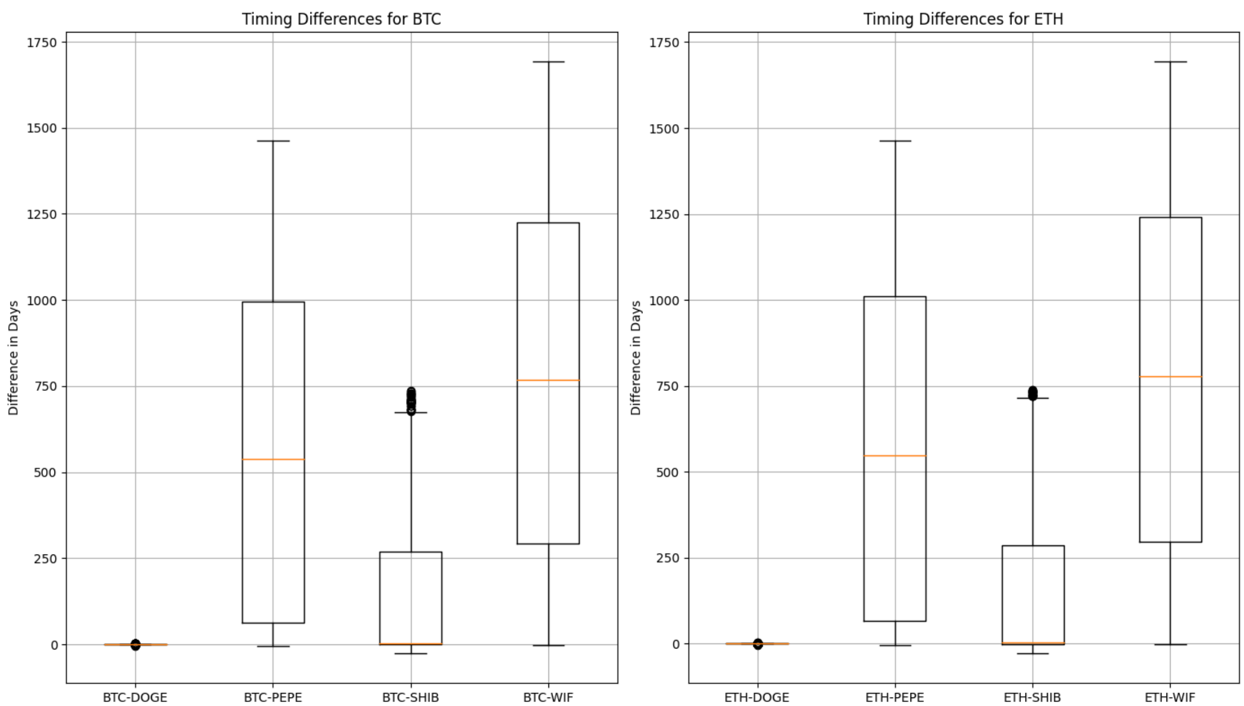

Figure 11: Box Plots of Timing Differences in Reversal Dates Between Major Cryptocurrencies and Memecoins

Linear Regression Analysis of Volume Predicting Price Action

The linear regression analysis showed different levels of predictive power of trading volume on price action across various cryptocurrencies. For major cryptocurrencies like BTC and ETH, R-squared values were low (0.081 and 0.107), indicating that volume has weak predictive power for their prices. In contrast, Dogecoin (DOGE) had a higher R-squared value (0.325), indicating moderate predictive power. The scatter plot for DOGE demonstrates a clearer linear relationship between volume and price than BTC and ETH.

Newer memecoins like PEPE and WIF exhibit stronger relationships. PEPE has a high

R-squared value (0.664), and WIF has the highest R-squared value (0.688) among the tokens analyzed. The scatter plots for both PEPE and WIF showed tight clustering around the regression lines, indicating that volume is a significant predictor of their price movements. Shiba Inu (SHIB) also shows moderate predictive power with an R-squared value of 0.352. The scatter plot for SHIB revealed a clear trend, indicating a moderate linear relationship between volume and price, as shown in Figure 12.

In summary, newer memecoins like PEPE and WIF show high predictive power of volume on price action, suggesting that trading volume significantly influences their price movements. DOGE and SHIB exhibited moderate predictive power, while BTC and ETH had low predictive power, indicating that other factors may be more influential in driving their price changes.

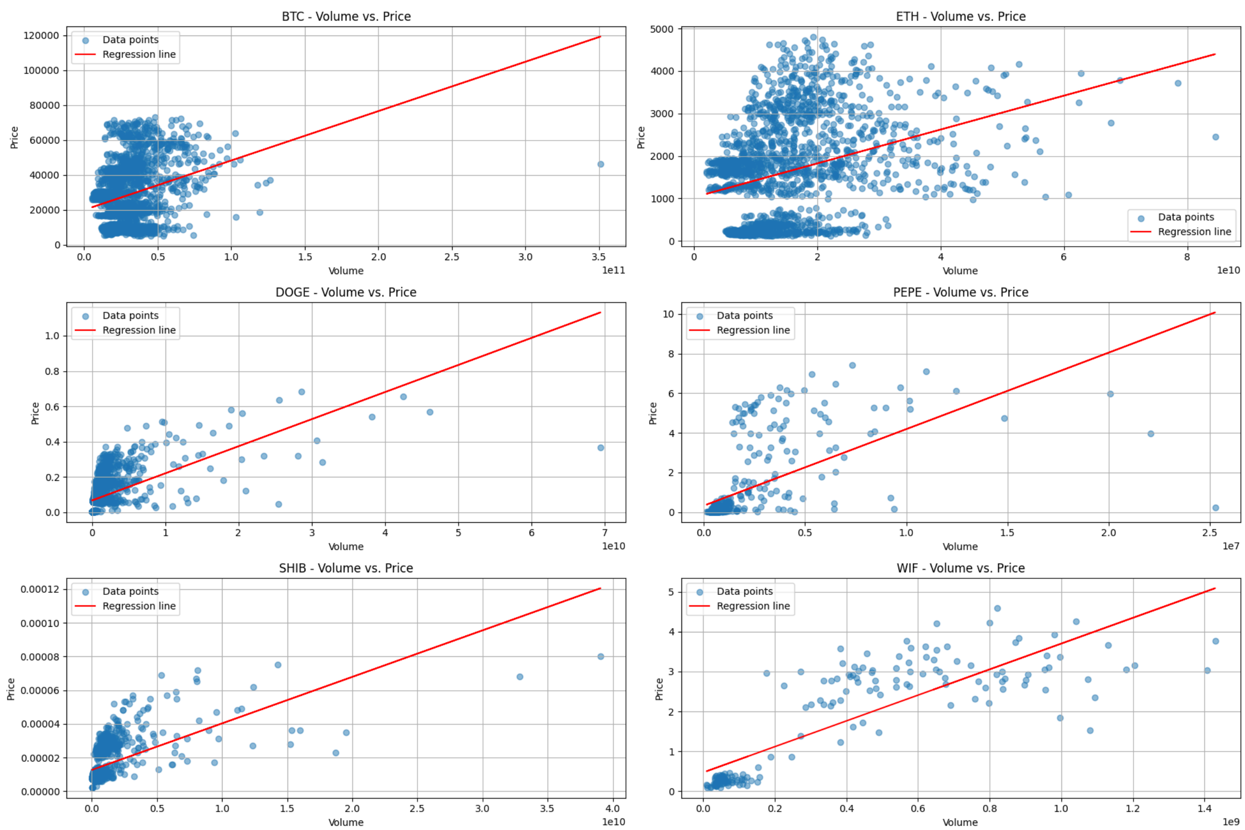

Figure 12: Linear Regression Analysis of Trading Volume Predicting Price Action for Cryptocurrencies

Linear Regression Analysis with Volume as a Leading Indicator

The analysis reveals that transforming volume into a leading indicator does not significantly improve its predictive power for price changes in the analyzed tokens. For BTC, ETH, DOGE, and WIF, the R-squared values are extremely low, indicating that the previous day's volume change has virtually no predictive power for the current day's price change. Specifically, BTC and ETH show no clear relationship between volume change and price change, as indicated by their very low R-squared values. DOGE also exhibits a weak relationship, while WIF shows no clear relationship, confirmed by the scatter plots. SHIB's R-squared value is higher than the others but still low (0.107), suggesting a weak predictive relationship between the previous day's volume change and the current day's price change. The scatter plot for SHIB shows some pattern, but the overall relationship remains weak. PEPE's regression did not converge, possibly due to data issues or an insufficient number of valid data points, and its scatter plot displays a highly scattered distribution, indicating no clear relationship.

The scatter plots and regression lines for each token visualize the relationship between the previous day's volume change (in percentage terms) and the current day's price change (in percentage terms). For BTC and ETH, the plots show no clear relationship, aligning with the low R-squared values. DOGE's scatter plot indicates a weak relationship, while PEPE's scattered distribution underscores the lack of a clear pattern. SHIB shows a weak but noticeable trend, and WIF's scatter plot confirms the absence of a clear relationship. These visualizations confirm the regression analysis results, illustrating the weak or nonexistent predictive power of previous day's volume change on the current day's price change for these tokens as shown in Figure 13.

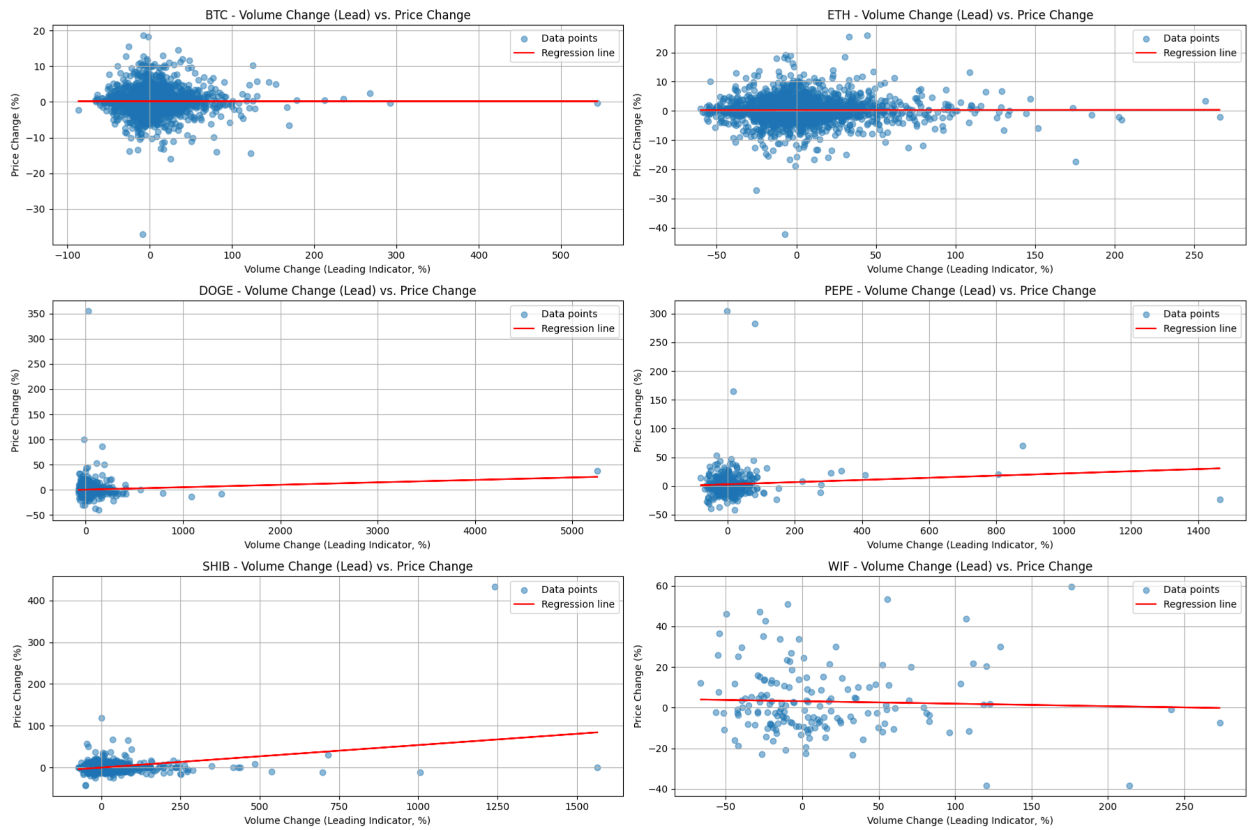

Figure 13: Scatter Plots of Previous Day's Volume Change vs. Current Day's Price Change for Cryptocurrencies

IX. CONCLUSION

In conclusion, this project combined cutting-edge modeling techniques with practical considerations to thoroughly assess the performance of a moving average crossover approach across a variety of cryptocurrencies. The Moving Average Crossover Strategy applied to six cryptocurrencies yielded varying effectiveness. WIF emerged as the best-performing asset, with an ROI of 2.8260, meaning that for every dollar invested, there was a return of 2.826 dollars, and the highest Sharpe Ratio of 0.1912, indicating strong returns with minimal risk. DOGE showed the highest ROI at 8.8408, implying substantial gains, but also exhibited significant volatility, as evidenced by a high Maximum Drawdown of -109.15%. This highlighted its potential for high returns coupled with substantial risk. Both BTC and ETH benefit from positive news events, but the effect is more pronounced and quicker for BTC, while ETH sees a delayed positive impact. Both cryptocurrencies experience significant and immediate price drops following negative news, with BTC's decline deepening over time and ETH's decline showing some stabilization after a week. These insights emphasize the importance of considering both market sentiment and technical strategies when evaluating cryptocurrency investments, as they can significantly influence asset performance and risk profiles (Chen & Guestrin, 2016; Ke et al., 2017).

HMMs provided insights into market states, identifying bull, bear, and stagnant periods for each cryptocurrency. BTC and DOGE were predominantly in bull markets, while ETH, PEPE, and WIF were mostly in stagnant markets, and SHIB in a bear market. Monte Carlo simulations forecasted future price paths, highlighting potential performance and risk. BTC showed stability with limited growth potential, ETH indicated moderate growth with minimal volatility, and DOGE and SHIB demonstrated higher potential returns but increased volatility. PEPE and WIF exhibited poor performance with significant risks (Costa et al., 2015)(Mostafa et al., 2020).

The analysis of trading volume and price action revealed significant insights. Established memecoins like DOGE showed consistent timing differences with BTC (-0.18 days) and ETH (-0.17 days), while newer memecoins like PEPE and WIF exhibited higher variability and less predictable reversal timings, with mean differences of 572.18 and 580.58 days (PEPE) and 767.06 and 777.09 days (WIF) with BTC and ETH, respectively. Linear regression analysis indicated that trading volume has varying predictive power on price action. PEPE and WIF demonstrated strong predictive power with high R-squared values of 0.664 and 0.688, respectively. Precise predictions were made by DOGE and SHIB, whose R-squared values were 0.325 and 0.352, respectively. Meanwhile, as seen by their low R-squared values of 0.081 and 0.107, BTC and ETH demonstrated poor predictive potential. Transforming volume into a leading indicator did not enhance predictive power significantly. R-squared values for the previous day's volume change predicting the current day's price change were extremely low for BTC, ETH, DOGE, and WIF, with SHIB showing a slightly higher value of 0.107. PEPE's regression did not converge, highlighting its variability and unpredictability.

Our comprehensive strategy, which included statistical modeling, technical analysis, and outside variables like news headlines, worked well for comprehending and negotiating the intricacies of the cryptocurrency market. The results of the study underscore the significance of adaptive trading strategies customized to the distinct attributes of individual cryptocurrencies, facilitating well-informed investment choices and optimal risk mitigation. These observations offer a strong basis for upcoming studies and the formulation of new strategies in the always changing field of cryptocurrencies.

X. LIMITATIONS AND FUTURE STUDIES

Notwithstanding the thorough approach taken in this investigation, a number of limitations need to be noted. Given the unpredictability of factors like legislative changes and technical improvements influencing cryptocurrency markets, it is possible that the historical data utilized will not accurately reflect future market conditions. The Moving Average Crossover Strategy's inconsistent performance across several cryptocurrencies highlights the necessity for flexible approaches. The incorporation of news events based on past data might not correctly represent the mood of the market in real time. Additionally, Hidden Markov Models and Monte Carlo simulations, though robust, are limited by assumptions of normal distribution and historical data accuracy. The study's limitation on the number of cryptocurrencies examined restricts the generalizability of its conclusions.

To improve the accuracy of market trend and sentiment forecasts, future research should utilize real-time data and advanced machine learning algorithms. Enhancing news sentiment analysis with natural language processing could provide more immediate market insights. Hybrid models fusing machine learning and technical indicators could be created by future research to provide more flexible trading methods. The robustness of the results would increase if the dataset were expanded to cover a wider variety of cryptocurrencies and longer historical periods. Furthermore, analyzing various market circumstances, such as times of high volatility, may provide insightful information on risk management. The efficacy of bitcoin trading techniques will be increased by ongoing improvement and the addition of additional data sources.

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